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SUSTAINING DEVELOPMENT AND POVERTY REDUCTION: PROMOTING GROWTH WHERE IT COUNTS

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ABSTRACT

We examine the relationship between the sectoral composition of economic growth and poverty reduction for the period 1987 to 2006 at a regional level for a cross section of developing countries. We also provide a comparison of the estimated sectoral GDP elasticities of poverty. We present evidence that growth in services is twice as effective as growth in both agriculture and industry in reducing absolute poverty. However, these results vary substantially across different income levels and regions. We argue that such a result warrants the attention of post-2015 development agencies given the interrelationship between drivers of economic growth, job creation and poverty reduction.

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INTRODUCTION

"The unfinished business of the twenty-first century is the eradication of poverty." – *Juan Somavia, United Nations World Summit for Social Development, 1995.*

Delivering on lessons learned from the Millennium Development Goals (MDGs) experience, the United Nations (UN) has facilitated an unprecedented outreach effort to people all over the world to express their priorities as input towards the post-2015 development agenda. The top priorities that emerged from the "Global Conversation" involving about 5 million people include (i) better education, (ii) better healthcare, (iii) better job opportunities, (iv) honest and reputable government, and (v) affordable and nutritious food (UN, 2014a). Almost all of these concerns can be linked to economic performance. Strong and sustainable economic growth may deliver jobs and improve the affordability of the other needs. The UN's big five "transformative shifts" listed as (i) leave no one behind; (ii) put sustainable development at the core; (iii) transform economies for jobs and inclusive growth; (iv) build peace and effective, open and accountable public institutions; and (v) forge a new global partnership, also depend largely on economic performance especially growth that creates jobs for people (UN, 2014b).

Under the MDGs, poverty has been reduced but not eradicated. The post-2015 development plan is firming towards poverty eradication not merely to reduce it. One of the most widely held beliefs in development economics is that rapid and sustained economic growth is necessary for lifting living standards which in turn is necessary if poverty is to be eradicated. Various cross-country analyses (Besley and Burgess 2003; Dollar and Kraay 2002 and Lopéz 2004), and cross regional and time series comparisons (Ravallion and Chen 2004; Ravallion and Datt 2002) can be cited in support of this.

In this context, debates on poverty alleviation and eradication have tended to focus on the best means of achieving or accelerating growth rates. This approach is reflective of the 'trickle down' theory which dominated development thinking in the 1950s and 1960s. The theory implies that the benefits of growth accrue first to the rich. Then in a second round the poor begin to benefit when the rich start spending their gains (Kakwani and Pernia 2000: 2). The assumption is that wealth will 'trickle down' to the poor of its own accord; thus growth, irrespective of its nature, is good for the poor (Kakwani and Pernia 2000: 2).

More recently, the development community has shifted its focus from fostering any economic growth per se to achieving 'shared growth' – growth with a maximum pay-off in terms of poverty reduction (Christiaensen et al 2006:2*). "There is not only concern on how fast the 'national pie' expands but specifically, how the increment to the national pie is distributed"* (Pernia 2006:1). Such growth enables the poor to actively participate in and significantly benefit from economic activity (Kakwani and Pernia 2000:2). The increasing focus on the relevance of inclusive growth has been supported by mounting evidence of considerable heterogeneity in the poverty-growth relationship across the globe (Loayza and Raddatz 2006:2). Understanding the sources of divergence is a growing area of investigation and undoubtedly provides key insights into the formulation of inclusive and sustainable national and global growth policies post-2015.

The literature has traditionally concentrated on socio-economic conditions as determinants of the growth-poverty nexus. Wealth and income inequality, literacy rates, urbanisation levels, mortality rates, etc. have been found to influence the degree to which growth reduces poverty (Christiaensen et al 2006:2). Hence, policies that explicitly target these 'initial conditions' are argued to allow for greater inclusive growth and ultimately to stimulate greater poverty alleviation.

A different, albeit complementary perspective which this study will pursue is the "pattern of growth" as a source of heterogeneity in the poverty-growth relationship. This notion has gained increasing attention over recent years. Explicitly, questions have been raised as to how the sectoral composition of growth affects its capacity to reduce poverty in different regions or locations around the world (Loayaz and Raddatz 2006:1). A stronger sectoral emphasis is also required to give practical guidance to policy makers who must make decisions about the allocation of public resources and foreign aid. The sectors that have the strongest impact on a decline in poverty must be identified and receive appropriately larger investment.

The need to resolve these issues has become all the more pressing as the global community refocuses its fight to eradicate poverty by 2030 without leaving anybody behind.In light of the above, the primary objectives of this paper are to examine whether the "pattern or composition of growth" matters with respect to poverty reduction in a cross section of developing countries and whether the results hold across different developing regions, time periods and income levels.

The rest of the paper is organized as follows. Section two examines the theoretical reasons as to why growth in different sectors may yield different poverty reducing effects. Section three will discuss the data sources and the empirical methodology. Section four will present results and discussion and section five concludes with policy implications and future research suggestions.

THE COMPOSITION OF GROWTH AND POVERTY REDUCTION

Aggregate growth equates to employment creation and expansion, which increases earning opportunities. This fuels growth in total, real income per head which is a prerequisite to the betterment of livelihoods and transitions out of poverty. Importantly, aggregate growth can be disaggregated into growth in the major productive sectors of the economy (e.g. agriculture, services and industry). Thus, sector specific growth can also determine growth in total, real income per head and therefore living standards. This hints to the relevance of the sectoral composition of growth for poverty reduction.

The contribution of growth to poverty declines can differ across sectors for several reasons. Suryahadi et al (2009) suggest that while the direct impact of a sector's growth on poverty is likely to be small due to its dependence on the sector's population share, its indirect effect may be much greater because of labour mobility, and the linkages between the sector's growth with growth in other sectors (Suryahadi et al. 2009:109). Further, growth differences in the sectoral growth-poverty relationship may arise because firstly, capturing the benefits of growth may be easier for the poor if it occurs where they are located— that is, where the geographical distribution of growth and poverty coincide (Christiaesen and Demery 2007:13).

METHODOLOGICAL FRAMEWORK

The framework used by Hasan and Quibria (2004) is adopted and extended for the analysis. In line with previous studies, this model allows for a comparison of the GDP elasticities of poverty across sectors, income groups, regions and time periods.

Dependent Variable

The dependent variable is absolute poverty, defined as the total number of people living below a specified minimum level of real income, usually an international poverty line. This measure is chosen because of its prominence in literature as well as in policy making circles (Loayaz and Raddatz 2006:9, 19). From a policy perspective, a key objective is to identify the proximate causes of transitions out of poverty which implies a focus on changes in the headcount because that is a measure of the number of people moving out of poverty (Warr 1998:17).

Independent Variables

Aggregate and sectoral growth

Economic growth is posited to have a negative relationship with absolute poverty – i.e. as growth increases, poverty will fall (Besley and Burgess 2003; Dollar and Kraay 2002, Lopéz 2004, Ravallion and Chen 2004; Ravallion and Datt 2002). Aggregate growth fosters both employment creation and expansion. This increases earning opportunities for all members of society and allows average incomes to rise. In particular, the main sources of growth from the standard production function – the accumulation of human and physical capital and technological change – generates increases in average incomes, which are particularly relevant for the poor.

Importantly, aggregate growth can be disaggregated into growth in the major productive sectors of the economy for a more detailed analysis and targeted policy.

Inequality

Growth reduces poverty but the degree to which this occurs will be conditioned by the level of inequality. Specifically, poverty will be more responsive to growth the more even and sustain the income distribution (Lucas and Timmer 2005:3). An important implication of this is that growth will only translate into significant poverty reduction or eradication if the distribution of income does not deteriorate (Ravallion 2001:13).

The Gini Index (or coefficient) is conventionally used to measure changes in inequality. It lies between 0 and 100, the former indicating that every person has the same income (perfect equality) while for the latter, the richest person has all the income (perfect inequality). Though it has been acknowledged to be rather crude, with one-dimensional characterisations of distribution, the Gini Index represents the only means of looking at the relationship between inequality and poverty for a broad range of countries (Besley and Burgess 2003:11).

The Model

Based on the above, this study hypothesises that the degree of poverty in any country depends on two primary factors: the average income level of the country and the extent of income inequality.

$$P=F(Y,I) \qquad (1)$$

where P is poverty incidence, Y is income, I is the level of inequality. Despite the theoretical arguments about the importance of income distribution in reducing poverty, the majority of the reviewed literature does not include an inequality measure in the analysis of the sectoral composition of growth and poverty reduction. This paper explicitly attempts to correct for this.[1] Drawing on Equation (1), a plausible regression model is of the form:

$$P_{it}=\alpha+\beta_i Y_{it}+\delta_i G_{it}+\varepsilon_{it} \qquad (i=1\ldots N;\ t=1\ldots T) \qquad (2)$$

where P_{it} is headcount poverty; Y_{it} denotes *GDP* per capita; G_{it} is the Gini Index; ε_{it} is a random error term; the subscripts i and t denote the country and year respectively; and lastly α, β_i and δ_i are the parameters to be estimated. However, because the current paper undertakes a cross country analysis, it is necessary to control for country heterogeneity – i.e. behavioural differences between countries and over time. Therefore, a second error term u_i is included in the model to account for unobserved effects:

$$P_{it}=\alpha+\beta_i Y_{it}+\delta_i G_{it}+u_i+\varepsilon_{it} \qquad (i=1\ldots N;\ t=1\ldots T) \qquad (3)$$

Importantly, u_i represents all the factors that can affect a country's poverty incidence but do not change over time such as geographical features, demographic features (age, race and education), cultural and historical factors (Wooldridge 2002:439).[2] Thus, u_i enables one to control for factors not explicitly taken into account (Wooldridge 2002:439). We estimate the double log model or the 'constant elasticity model' because the growth and inequality elasticities of poverty are key magnitudes of interest and because of their interpretative ease for policymakers. Further, the double log functional form has been applied extensively in growth-poverty studies and we want to remain consistent with the literature[3] Equation (3) is therefore respecified in double log form as:

$$lnP_{it}=\alpha+\beta_i lnY_{it}+\delta_i lnG_{it}+u_i+\varepsilon_{it} \qquad (i=1\ldots N;\ t=1\ldots T) \qquad (4)$$

The use of the log-log specification is further justified by the patterns revealed in the scatter plots of the regressions of poverty on GDP per capita and log(poverty) on log(*GDP* per capita); shown in Figure 1 and 2, respectively.

Figure 1 Scatter plot - Poverty and GDP

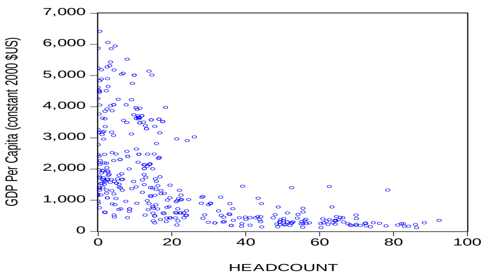
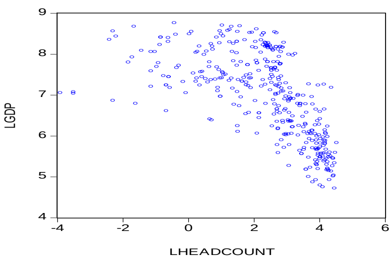


Figure 2 Scatter plot – ln(poverty) and ln(GDP)



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Poverty and sectoral growth

Following the specification of Hasan and Quibria (2004) but extending it through the inclusion of an inequality measure, Equation (4) can then be re-written as: [4]

$$lnP_{it}=\alpha+\beta_i^A lnY_{it}^A+\beta_i^S lnY_{it}^S+\beta_i^I lnY_{it}^I+\delta_i lnG_{it}+u_i+\varepsilon_{it} \qquad (i=1...N;\ t=1...T) \qquad (5)$$

where the superscripts *A*, *S* and *I* denote the agricultural, services and industrial sectors; all other variables are as previously defined. The rationale for this specification is that if growth in each sector affects poverty equally ($\beta=\beta_i^A=\beta_i^S=\beta_i^I$) then equation (5) will reduce to equation (4). Thus by testing the null of the coefficients all being equal (H_o: $\beta = \beta_i^k$ for all *k*), one may test directly whether the sectoral composition of growth affects the rate of poverty reduction.

Income, regional and time period analysis

We attempt to improve upon past aggregate, cross country studies by exploring whether the sectoral composition of growth matters for poverty reduction across income, regional and time dimensions. To examine results across differing income levels, the sample is split into groups based on the country's GDP per capita and separate regressions are run for the low, low-middle and upper-middle income countries.[5] Similarly, for the regional dimension the sample is split into regional groups –Eastern Europe, Latin America and Caribbean, Asia (East and South Asia) and Sub Saharan Africa.

The Data

Long time series data for individual developing countries is generally not available especially for poverty. To circumvent this problem, this study pools cross country data (for 82 developing countries) to investigate the composition of growth / poverty nexus. We use the World Bank's 2008 GNI per capita classification of economies which is within the scope of our data. Headcount statistics were taken from the World Bank's Povcal Net database 2009.[6] Importantly, *national* headcount figures are used to avoid potential biases associated with urban or rural measures which may present inaccurate reflections of national poverty incidence. As argued by Deininger and Squire (1998:569) the relationship between urban and rural poverty within the same country is far from static. Therefore it is not valid to draw inferences about national poverty from information on poverty within a subgroup of the population (Deininger and Squire 1998:569).[7]

For countries that only have urban and rural headcount figures, this study derives national figures as a population weighted summation of the rural and urban headcount.[8] The following formula is employed:

$$\text{National Headcount}_i = \text{Rural H}_i \times \frac{\text{Rural Pop}_i}{\text{Total Pop}_i} + \text{Urban H}_i \times \frac{\text{Urban Pop}_i}{\text{Total Pop}_i}$$

Rural H_i and urban H_i are rural and urban headcount figures for country *i*, taken from Povcal (World Bank 2009). Rural pop_i and urban pop_i are the rural and urban population, sourced from the Food and Agriculture Organisation population statistics (FAOSTAT) database (UN 2010). Total pop_i denotes the total population, growth is measured by changes in GDP per capita in 2000 constant \$US, and sector specific growth measured by sectoral value added GDP in 2000 constant \$US figures for agriculture, industry and services are all sourced from the World Development Indicators (WDI) 2007. These figures are transformed into per capita terms using population figures from the same database. Data on the Gini Index (or coefficient) are taken from the Povcal database 2009. To ensure comparability between observations on the dependent and independent variables, the years for which aggregate and sectoral GDP data as well as Gini values are taken are matched to the corresponding years of data that are available for headcount poverty figures.

Estimation Procedure

Panel data estimation

In the absence of long time series poverty data for developing countries, national level time series data on each variable are pooled for a cross section of developing countries. These characteristics constitute that of panel data, which by definition, consists of a group of cross-sectional units who are observed over time. Panel data estimation is therefore carried out. It is necessary to highlight that the panel data set is unbalanced and unevenly spaced, with missing values arising in different years for different countries.[9] While unbalanced panel estimations are able to be carried out with the econometric software at hand (Eviews 7), many limitations arise, particularly concerning diagnostic testing. These are discussed under methodological issues.

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The unobserved effects model: Fixed and random effects estimation

A variety of techniques can be used to estimate the unobserved effects model from Equation (5). These include, first differencing and fixed or random effects estimation. In most applications, the main reason for collecting panel data is to allow for the unobserved effect u_i to be correlated with the explanatory variables (Wooldridge 2002:460). If this is the case, first differencing or fixed effects estimation can be used. However, this study does not employ first differencing because of the unbalanced and unevenly spaced nature of the data Fixed effects' testing is performed to test joint significance of the fixed effects estimates using the sum-of-squares (*F*-test) and the likelihood function (Chi-squares test). The test results presented in table 1 reject the null that cross section fixed effects are redundant and indicate that period fixed effects are redundant.

Table 1: Redundant Fixed Effects Tests
Test cross-section and period fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	8.653743	(81,247)	0.0000
Cross-section Chi-square	473.410720	81	0.0000
Period F	0.680617	(19,247)	0.8369
Period Chi-square	17.962779	19	0.5249

Based on the results from the fixed effects test, we proceed with random effects estimation. The Hausman (1978) test is employed to test for correlation between u_i and the explanatory variables in the cross section and period dimension. Results are shown in tables 2 and 3 respectively.

For cross section random effects, the test statistic (10.15) and the *p*-value (0.038) show that at the five percent level, the null hypothesis of no misspecification is rejected. Likewise, for period random effects, the test statistic (10.30) and the *p*-value (0.036) mean the null is again rejected at the five percent level. The conclusion is that random effects in both dimensions are inappropriate. In light of the above results, cross section fixed effects analysis is the preferred estimation technique for analysing the unbalanced panel data set.

Table 2 Correlated Random Effects - Hausman Test
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	10.153907	4	0.0379

Table 3 Correlated Random Effects - Hausman Test
Test period random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Period random	10.304783	4	0.0356

Methodological Issues

Given that panel data combines both cross section and time series data, issues relating to cross section and time series analysis need to be addressed.

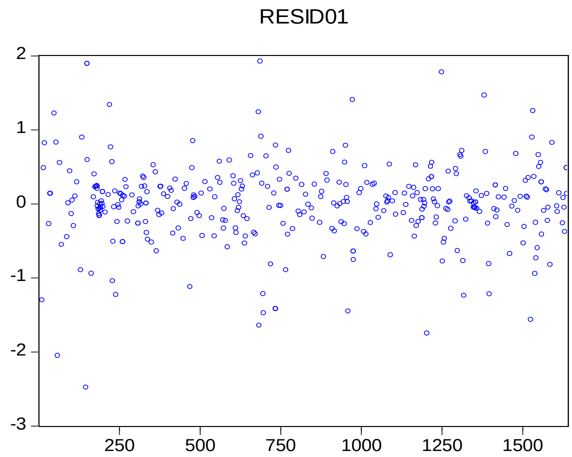
Panel unit root and cointegration tests

Stationarity is important in time series analysis to prevent spurious results.[10] However, Eviews requires balanced observations for panel unit root testing. Consequently invalid results are obtained when applied to the unbalanced and unevenly spaced data set. Panel cointegration tests are unavailable for the same reason. These are important limitations of the current paper. Hence, it is acknowledged that any empirical results should be interpreted cautiously.

Serial correlation tests and remedial measures

Serial correlation is typically associated with time series data.[11] In its presence, least squares estimators are not efficient[12] and the standard t and F tests become unreliable. A Durbin Watson statistic of 1.45 suggests the presence of serial correlation in the model. However, this measure is not always satisfactory.[13] Consequently, a visual examination of the residuals from Equation (4) is undertaken and presented in Figure 3. No distinct pattern emerges suggesting no autocorrelation (Gujarati 2006:429).[14]

Figure 3 Serial Correlation Test - Residual Plot



Despite the inconclusive nature of the above diagnostic tests it is still maintained that an attempt to correct for serial correlation is more desirable than leaving the possibility of its presence unchecked. The standard Prais-Winsten and Cochrane-Orcutt transformations for autocorrelation cannot be performed because they rely on the estimated autocorrelation coefficient ρ which cannot be obtained. In recent years, it has become popular to estimate models by OLS but to correct the standard errors for fairly arbitrary forms of serial correlation (and heteroskedasticity) (Wooldridge 2003:410). The White cross section method is selected as this estimation is robust to cross equation (contemporaneous) correlation in each cross section (Eviews 7 User's Guide: 504)[15]

Heteroskedasticity tests and remedial measures

Heteroskedasticity is usually found in cross sectional data.[16] As with serial correlation, least squares estimators are not efficient and t and F tests are unreliable (Gujarati 2006:397). Again, the conventional tests for heteroskedasticity are not available for panel equations; consequently, an attempt is made to manually detect for it using the Breusch-Pagan test.[17] The original specification is estimated by OLS and the squared residuals are obtained. The following auxiliary regression is run:

$$e_i^2=\alpha+\beta_i^A lnY_{it}^A+\beta_i^S lnY_{it}^S+\beta_i^I lnY_{it}^I+\delta_i lnG_{it}+v_{it} \quad (i=1 \ldots N;\ t=1 \ldots T) \quad (5)$$

The F and LM statistic are of interest. Both depend on the R-squared from regression (5). The calculated F statistic (11.49811) exceeds the critical F value (2.21);[18] therefore the null hypothesis of homoskedasticity is rejected. Similarly, the calculated LM statistic is 50.18922 and exceeds the critical value (11.0705). The null is again rejected.[19]

The reliability of the Breusch-Pagan test for unbalanced and unevenly spaced panel data is unclear.[20] Therefore, results must be interpreted cautiously. Nevertheless, there seems to be a strong indication of heteroskedatiscity.[21] Eviews can estimate a generalized least squares GLS specification assuming the presence of cross-section heteroskedasticity. To do so, cross section weights are chosen under GLS weights which allow for different residual variance for each cross section.

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Income, Regional and Time Period Methods

In line with the aggregate sectoral model, cross section fixed effects, with cross section weights and white cross section methods, are used in the regressions of each sub-sample under the income and regional analyses. This ensures comparability of results. However, for the time period analysis, the data set is not split because running separate regressions for individual time periods is problematic. In using panel estimation, the generation of sub samples causes many countries with two observations or those with a single observation occurring in any one time period to be dropped. Thus, the dummy variable technique is used on the pooled data testing whether or not the three periods are subject to different regression functions. Cross section weights and the white cross section method are again applied as in the aggregate model.

It is also worth noting that for the regional analysis, a further decomposition is engaged in for Asia. East and South Asia were originally pooled together due to a lack of sufficient observations for each region individually. However, given that the East and South have been characterized by significantly divergent growth experiences it is possible that each region is subject to different regression functions. Dummy variables are again employed to test this hypothesis.

RESULTS AND DISCUSSION

Poverty and Aggregate Growth

The estimation output for regression of poverty on GDP per capita and the Gini is reproduced in table 4. Data on sectoral specific GDP values are summated to give aggregate GDP Value added per capita, which is used in place of GDP per capita to compare robustness of results.

All coefficients are statistically significant and signs are consistent with a priori expectations. Regression one suggests that if GDP per capita increases by one percent, headcount poverty decreases by 1.71 percent on average. Secondly, if inequality increases by one percent, the headcount increases by 2.21 percent. The adjusted R-squared (0.95) attests to a high goodness of fit and suggests that approximately 94 percent of the total variation in headcount poverty can be explained by aggregate growth and inequality. Similar results are found for regression two, though the GDP elasticity and Gini elasticity are marginally lower and the adjusted R-squared remains high.

Table 4 Poverty and Aggregate Growth

Model 1	**Coefficient**	**Model 2**	**Coefficient**
C	5.90673***	C	5.82491***
	(5.540665)		(5.742034)
LOG(GDP)	-1.707627***	LOG(GDPVA)	-1.594373***
	(-17.23418)		(-18.01103)
LOG(GINI)	2.210986***	LOG(GINI)	1.990721***
	(9.955464)		(8.187198)
Adjusted R squared	0.945116	Adjusted R squared	0.941217
Observations	352	Observations	352
Cross Sections	82	Cross Sections	82

Source: Author's Calculations. Note that t-statistics are reported in parenthesis and adjusted for serial correlation. * denotes significance at the 10% level; ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Poverty and the Sectoral Composition of Growth

The output for the regression of poverty on sector specific growth and the Gini is shown in table 5. All GDP elasticities have negative signs while the Gini elasticity is positive, consistent with a priori expectations; all coefficients are statistically significant at the one per cent level. The results are somewhat contrary to initial expectations, showing that a one percent increase in services growth will reduce headcount poverty by roughly 0.87 percent, while for a one percent increase in agricultural and industrial growth, the headcount will only decline by 0.47 and 0.42 percent, respectively. The Gini elasticity is slightly greater than in the previous regression; the adjusted R-squared remains high. Therefore, the results suggest that while agriculture remains important to poverty reduction it offers the second highest return for poverty alleviation; its impact only marginally outstripping that of industrial growth. Services growth clearly displays the greatest potential and is approximately twice as effective in lowering the headcount poverty as growth in all other sectors.

Table 5 Poverty and the Sectoral Composition of Growth

Model	**Coefficient**
C	3.961789***
	(3.614966)
LOG(AGVA)	-0.472467***
	(-3.754697)
LOG(SERVVA)	-0.867069***
	(-3.915368)
LOG(INVA)	-0.424081***
	(-2.714956)
LOG(GINI)	2.253395***
	(9.387285)
Adjusted R squared	0.945116
Observations	352
Cross Sections	82

Source: Author's Calculations.
Note: t-statistics are reported in parenthesis and adjusted for serial correlation.
* denotes significance at the 10% level; ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Poverty and the Sectoral Composition of Growth by Income Level

The fixed effects regression of poverty on sector specific growth and the Gini is run on three separate samples based on countries' income levels. [22] Results are presented in table 6. For low income countries, the estimated agricultural GDP elasticity is negative but statistically insignificant, suggesting that it has no impact on absolute poverty. The coefficient for services is negative and significant, implying that a one percent increase in services growth will result in a poverty decline of 0.90 percent. Interestingly, the industrial GDP elasticity is positive and significant suggesting that a one percent increase in industrial growth will actually increase headcount poverty by 0.15 percent. The inequality elasticity shows that a one percent rise in inequality leads to a 0.21 increase in poverty incidence. Thus, growth in services generates the largest poverty declines, which is consistent with the findings of the aggregate sectoral growth model.

For low middle income countries both services and industrial growth are negative and statistically significant. Industry has a larger effect than services in generating poverty declines, with a one percent increase in growth relating to a 0.89 percent decline in the headcount. The inequality elasticity is again positive but substantially higher than for low income countries.

In contrast to the previous income groups, growth in agriculture is both negative and significant for upper middle income countries – one percent growth in the agriculture generates a 0.87 percent decline in the headcount poverty. Moreover, the services coefficient is negative but insignificant, suggesting that services growth does not impact poverty incidence. Industrial growth is shown to offer the highest return for poverty reduction as in low middle income countries. Here, an increase in industrial growth of one percent will lead to a 1.21 percent decline in the headcount. The estimated coefficient for inequality is still positive though slightly lower than for low middle income countries.

These finding both support and contrast those of Christiaensen et al. (2006). The 2006 study holds that only agricultural growth affects poverty reduction in low income countries while both agricultural and non-agricultural growth (services and industry combined) offer scope for poverty alleviation in middle income countries, the former having a greater impact. Conversely, this study finds that services growth is the key to poverty reduction in low income countries. For low-middle income countries only non-agricultural sectors promote poverty declines, with industry deemed the leading sector for poverty alleviation. For upper middle

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income countries, results are somewhat more reflective of Christiaensen et al (2006)'s findings – both agricultural and industrial growth generate poverty declines but industry again has the highest effect.

Table 6 Poverty and the Sectoral Composition of Growth by Income Level

	Low Income Countries	**Low-Middle Income Countries**	**Upper-Middle Income Countries**
C	6.681932***	-3.639360	3.014048
	(23.67584)	(-1.564537)	(0.906995)
LOG(AGVA)	-0.017383	-0.235830	-0.866191***
	(-0.166668)	(-0.790296)	(-2.936808)
LOG(SERVVA)	-0.895748***	-0.565888**	-0.463428
	(-10.73921)	(-2.2033312)	(-1.336040)
LOG(INVA)	0.152764***	-0.890794***	-1.207952***
	(9.146765)	(-3.596273)	(-2.891235)
LOG(GINI)	0.209961***	4.224994***	3.750073***
	(6.434293)	(7.272428)	(6.209945)
Adjusted R-Squared	0.971886	0.914259	0.91951
Observations	91	145	116
Cross Sections	28	33	21

Sources: Author's calculations: t-statistics are reported in parenthesis and adjusted for serial correlation. * denotes significance at the 10% level; ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Poverty and the Sectoral Composition of Growth by Region

The regression of poverty on sector specific growth and the Gini is run on five separate samples based on the developing regions of the world. The results are presented in table 7.

For Eastern Europe, the coefficients for agriculture and industry are both negative and significant at five percent level (-1.44 and -1.77 respectively). Thus, industrial growth offers a higher return in terms of poverty reduction, albeit only marginally. The coefficient for services is found to be positive but is insignificant, which contrasts the results of the aggregate sectoral model. The inequality elasticity is quite high showing that a one percent increase in inequality will on average result in a 5.09 increase in poverty.

The estimated growth elasticities are reasonable considering Eastern Europe is more industrialised and 'developed' compared to other developing regions and thus may be characterised by a larger industrial sector with a greater ability to generate poverty declines. Agriculture also remains highly important for reasons previously discussed. Farm production structures in Eastern Europe typically consist of commercially oriented, private family farms as well as rising corporate and collective farm structures (Sarris et al 1999:1). High levels of output, productivity, wages and income exist, therefore fuelling movements out of poverty.

For Latin America, the services growth has by far the largest effect on poverty alleviation with a one percent increase generating a 2.17 percent decline in the headcount. Most surprisingly, the coefficient for agriculture is significant at the five percent level but it is positive. It suggests that a one percent increase in agricultural growth actually leads to a 0.56 percent rise in the headcount poverty. Meanwhile, the inequality coefficient and adjusted R-squared though lower than for Eastern Europe, both remain reasonably high. The above findings are largely consistent to that of Hasan and Quibria's (2004) results for Latin America.

The finding for agriculture is perplexing and may require some discussion. Commercial farming is more prevalent in Latin America than Asia and Africa, suggesting that agricultural growth may play a role in poverty alleviation. However, a pattern of agricultural dualism known as *latifundio-minifundio* characterises the region and offers a plausible explanation. Latifundios are very large landholdings and the owners are wealthy, while minifundio owners are impoverished peasants (Todaro and Smith 2009:441).[23] In this context, agricultural growth and its benefits accrue predominantly to the wealthy landowners, bypassing the poor. The perverse effect on income equality through the further concentration of income amongst the rich generates increases in the incidence of poverty.

Table 7 Poverty and the Sectoral Composition of Growth by Region

	Eastern Europe	**Latin America & the Caribbean**	**Asia (East and South)**	**Sub-Saharan Africa**	**Middle East & North Africa**
C	-5.425054*	1.491594	2.980661	3.430632***	11.22274**
	(-1.973354)	(0.636003)	(0.997622)	(2.802766)	(2.348284)
LOG(AGVA)	-1.437746**	0.556254**	0.596027	0.268487	-0.175090
	(-2.171760)	(2.142647)	(0.2955)	(1.375393)	(-0.232335)
LOG(SERVVA)	0.923161	-2.146804***	-0.223230	-0.787092***	-0.985519
	(1.341020)	(-4.978767)	(-0.700686)	(-5.433384)	(-0.724928)
LOG(INVA)	-1.771444***	0.176904	-0.846613***	0.072368	-1.347773
	(-2.672820)	(0.674440)	(-2.557257)	(1.071813)	(-1.198441)
LOG(GINI)	5.097561***	3.000612***	0.840803	0.747957***	1.441052
	(12.17863)	(6.434982)	(1.667656)	(7.093101)	(1.511307)
Adjusted R-Squared	0.941793	0.804045	0.940233	0.921452	0.818603
Observations	64	120	66	78	24
Cross Sections	18	18	14	24	8

Sources: Author's calculations t-statistics are reported in parenthesis and adjusted for serial correlation. * denotes significance at the 10% level; ** denotes significance at the 5% level and *** denotes significance at the 1% level.

For Sub-Saharan Africa, service is the only sector in which growth affects absolute poverty. The estimated coefficient is -0.79 and is significant at the one percent level. Meanwhile, both the coefficients for agriculture and industry are positive but insignificant. These results refute those of Hasan and Quibria (2004), who find that agricultural growth alone reduces poverty incidence in Sub-Saharan Africa with a coefficient of -0.32. However, current estimates are plausible given the prevalence of subsistence agriculture throughout the region, the implications of which are noted above. Also, given the low levels of industrialisation in the region, the result for industry is unsurprising. The coefficient for Gini remains significant for Africa but is substantially lower than that of Eastern Europe and Latin America.

For the Middle East, although all coefficients are consistent with a priori expectations, they are all statistically insignificant. The inadequacy of these results is possibly due to the limited amount of observations included in the sample, preventing accurate detection of the underlying relationships between poverty, sectoral GDPs and inequality.

For Asia, only industrial growth has an impact on poverty reduction. The industry coefficient suggests that one percent increase in industrial growth will on average promote a 0.85 percent reduction in headcount poverty. These results may reflect the interplay of policies and institutions in Asian region which have been highly conducive to rapid industrialisation[24] allowing industrial growth to exert the strongest and most beneficial impact on poverty. The inequality elasticity is positive but insignificant. These results mirror the findings of Hasan and Quibria (2004) for East Asia, where industrial growth alone was found favourable to poverty reduction (-1.31).

It is acknowledged that observations for Asia involve pooled observations for both East and South Asia; individually the sample sizes for each were unappealingly small at 46 and 20 observations, respectively. However, there is a distinct possibility that the two regions are subject to different regression functions. Thus, dummy variables are employed to test the null hypothesis that the two populations follow the same function. The results are displayed in table 8.[25]

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Table 8 Poverty and the Sectoral Composition of Growth – East and South Asia

	East Asia	**South Asia**
C	12.3744***	12.37440***
	(5.581841)	(5.581841)
LOG(AGVA)	0.608637***	-1.501772***
	(3.115247)	(-3.712900)
LOG(SERVVA)	- 1.282623***	-1.282623***
	(-4.260532)	(-4.260532)
LOG(INVA)	0.255105	0.255105
	(0.971116)	(0.971116)
LOG(GINI)	-1.741064***	-0.278376***
	(-3.647207)	(-4.44882)
Adjusted R Squared	0.917685	
Sample Observations	46	20
Total Observations	66	
Cross Sections Included	14	

Source: Author's Calculations: t-statistics are reported in parenthesis and adjusted for serial correlation. * denotes significance at the 10% level; ** denotes significance at the 5% level and *** denotes significance at the 1% level.

The results for East Asia indicate that agricultural growth has a significant but positive impact on poverty reduction, contrary to a priori expectations. Specifically, one percent growth in agriculture will increase poverty by approximately 0.61 percent. This seemingly odd result can be explained by the problems of fragmentation and the cumulative subdivision of peasant land in Asia (Todaro and Smith 2009:447) caused by the rapid rate of population growth in the region. In contrast, the coefficient for services is more encouraging. It is significant at the one percent level and indicates that one per cent growth in services will decrease poverty by 1.28 percent on average. The coefficient for industry is positive but statistically insignificant. The inequality elasticity is significant but it is negative (– l.74) which suggests increasing inequality.

In theory, it is possible that growth could generate higher inequality, causing its benefits to accrue to the rich and bypass the poor. Aggregate poverty incidence is then likely to rise. This phenomenon has been referred to as 'immiserizing' growth (Kakwani 2001:3) and is founded on Kuznets Hypothesis (Kuznets 1955) which states that in the early stages of growth, income distribution tends to worsen and improves only during later stages. Although some studies reject Kuznets hypothesis and conclude that growth per se raises mean income without making income distribution more or less equal (Adams 2004:1991; Besley and Burgess 2003: 11),[26] the East Asian result appears to follow Kuznets hypothesis.

The results for South Asia show that there is no difference in the intercept term. However for agriculture the sign is negative and consistent with a priori expectations. A one percent increase in agricultural growth will yield a 1.5 percent reduction in headcount poverty. The coefficient for services remains the same, demonstrating there is no statistical difference between the effect of services growth in East and South Asia. Likewise, the industry coefficient remains the same – positive and insignificant. The inequality elasticity is significant but again has a negative sign, though the impact on poverty is smaller at – 0.28.

Therefore, the findings for the East and South Asian regression functions show a marked difference to the aggregate results for Asia. However, the new findings closely align with the findings of Warr (2002) for the Southeast Asia region. In particular, the results for South Asia mirror Warr's (2002) result in which both agriculture and services promote poverty reduction, with services yielding the larger coefficient (-1.148) compared with -0.476 for agriculture.

CONCLUSION

As admonished, the results should be interpreted cautiously given the methodological issues discussed in the paper. Nevertheless, the composition of growth is clearly shown to matter in poverty alleviation. A major implication of this is that traditional policies, which simply focus on the best means of achieving or accelerating overall growth, may not be sufficient to generate widespread poverty reduction. Sector specific policies that support those with a greater ability to generate poverty declines are crucial. It was found that, contrary to theoretical expectations, growth in agriculture does not always elicit the highest returns to poverty alleviation. Broadly speaking, growth in services was primarily identified as generating the strongest impact on poverty declines. However, it is found that results vary significantly across income, regional and time dimensions. In this light, the broad policy recommendations outlined below may need to be altered in regional and country-specific contexts.

POLICY IMPLICATIONS

The aggregate results suggest that policies geared towards the promotion of services growth can ensure the largest return in terms of poverty reduction. Moreover, because it is highly plausible that it is the informal services sector that is the most relevant to the poor, there is a strong imperative to redress the decades of neglect and hostility directed at this sector. For example, access to finance is a major constraint on informal sector activities. Microfinance institutions have been leading the way in providing enhanced credit access. Policy should therefore aim to foster their growth and find ways of making access beneficial to the poor. This would permit incumbent enterprises to expand, produce more profit and hence generate more income and employment. Training and access to improved technology would also have similar effects on poverty. However, the promotion of non-agricultural sectors must be undertaken cautiously due to unprecedented rates of urbanisation and the size of urban agglomerations now characterising the developing world.

In this context, we maintain that while non-agricultural growth may induce substantial poverty declines by transitioning those marginally below the poverty line, it may fail to target those living in extreme or chronic poverty. Thus, if meaningful poverty reduction is to take place and become self-sustaining, broad-based growth in agriculture and rural economy still appears to be essential.

Secondly, supportive policies must be in place to generate the incentives and economic opportunities to enable small cultivators and service operators to expand their output and raise their productivity. Reforms to trade, price and subsidy policies previously biased against agriculture are vital. Developed countries must also make efforts to open markets and work towards reforming agricultural protection policies. Improving developing-country access to developing-country markets (“South-South Trade”) could also help to ameliorate the problems of limited market access to developed countries.

The importance of redistributive policies to poverty reduction is also clear from the empirical findings of this paper. The conditions for sustained, pro-poor growth are closely tied to reducing the extent of income inequality. If this is neglected, the benefits of any recommended economic reforms can readily by-pass the poor. The most successful strategies to promote poverty reduction will combine policies conducive to pro-poor growth while simultaneously decreasing income disparities. Redistributive policies such as progressive income and wealth taxes, direct transfer payments to the poor and the public provision of goods and services should be strengthened. More radically, policy may advocate progressive redistribution of asset ownership (land reform is a classic example). Similar policies are also needed to target unequal access to education and income-earning opportunities (Todaro and Smith 2009:245).

FUTURE RESEARCH SUGGESTIONS

While this paper shows that the sectoral composition of growth affects the poverty reducing capacity of growth and identifies services as a leading sector in poverty alleviation, the results are limited for a number of reasons. Firstly, the unbalanced and unevenly spaced panel data used present methodological issues which limit the diagnostic tests applied. A greater exploration of diagnostic testing and remedial measures should be undertaken in future research to ensure greater accuracy and reliability in estimates. The study is also limited by data availability and especially poverty data. Nationally representative household surveys in developing countries should be taken at more regular intervals to allow for greater accuracy in the study of the poverty-growth nexus. Importantly, if sufficiently long time series data on poverty for individual countries becomes more available, future research should move towards country specific analysis. The formulation of country specific strategies should remain a top priority.

APPENDIX

List of Countries

Albania	China	Indonesia	Moldova, Rep.	Sierra Leone
Algeria	Colombia	Iran, Islamic Rep.	Mongolia	South Africa
Argentina	Costa Rica	Jamaica	Morocco	Swaziland
Armenia	Côte d'Ivoire	Jordan	Mozambique	Tajikistan
Azerbaijan	Dominican Republic	Kazakhstan	Nepal	Tanzania
Bangladesh	Ecuador	Kenya	Nicaragua	Thailand
Belarus	Egypt, Arab Rep.	Kyrgyz Republic	Sri Lanka	Tunisia
Bolivia	El Salvador	LAO PDR	Niger	Turkey
Botswana	Ethiopia	Lesotho	Nigeria	Uganda
Brazil	Gambia, The	Lithuania	Pakistan	Uruguay
Bulgaria	Georgia	Macedonia, FYR	Panama	Venezuela
Burkina Faso	Ghana	Madagascar	Paraguay	Vietnam
Burundi	Guatemala	Malawi	Philippines	Yemen, Rep.
Cambodia	Guinea	Malaysia	Poland	Zambia
Cameroon	Guyana	Mali	Romania	
Central African Republic	Honduras	Mauritania	Rwanda	
Chile	India	Mexico	Senegal	

ENDNOTES

[1] Indeed, Bourguignon (2003) acknowledges that a problem with many recent papers on the statistical relationship between growth and poverty reduction is the failure to take into account the poverty / mean-income / distribution nexus (Bourguignon 2003:6).
[2] Or, that more precisely, factors that are not exactly constant over time but are roughly constant over longer periods (e.g. five years) (Wooldridge 2002:439) .
[3] It is only for the double log model that the elasticity can be directly derived from estimates of the slope coefficients (Gujarati, 1995).
[4] Note Hasan and Quibria (2004) also differ in their use a smaller cross section of countries (45) and different data source for poverty than the current study. Data on per capita incomes is from the Penn World Tables and poverty data are obtained from HQK.
[5] Based on the Bank's classifications the groups are: low income, $975 or less; lower middle income $976 - $3 855; upper middle income, $3 856 - $11 905; and high income, $ 11 906 or more. Low-income and middle-income economies are classified as "developing". However, both the World Bank and this paper acknowledge that while the term is convenient for operation and analytical purposes, it is not intended to imply that all economies in the group are experiencing similar development. Due to data limitations especially on poverty statistics, we use data from 82 "developing" countries.
[6] In the calculation of the headcount index, the Bank currently uses international poverty line, set at $1.25 per person per day in 2005 constant prices. According to the World Bank, consumption of $1.25 a day in 2005 prices now represents the best estimate of the extreme poverty line based than the old "dollar a day" poverty line
[7] To remain consistent with the extant literature we use the same "welfare indicator" – either consumption per person or income per person – for the same country, over time (Ravallion and Chen 1997:363). Income measures at one date are not compared with consumption measures at another date.
[8] China, India and Indonesia all have urban and rural surveys from which nationally representative headcount poverty figures can be derived.
[9] Note the data set which this paper employs is defined as "short and wide." Indicating that there are many individuals observed over a relatively short period of time (usually where N is much larger than T).

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[10] Broadly speaking, a stochastic process is stationary if its mean and variance are constant over time and the value of the covariance between two time periods depends only on the distance or lag between the two time periods and not on the actual time at which the covariance is computed.[10] (Gujarati 2006:497).

[11] In technical terms, no autocorrelation means that the expected value of the product of two different error terms e_i and e_j is zero. Put differently, the assumption is that the disturbance term relationship to any observation is not related to or influenced by the disturbance term relating to any other observation. Note that it can occur in cross-sectional data in which case it is called spatial correlation (Gujarati 2006:428).

[12] I.e. do not have minimum variance. However, the OLS estimators do remain linear and unbiased.

[13] Eviews acknowledges that the Durbin Watson statistic can be difficult to interpret and for this reason it often recommends using other autocorrelation tests in preference to the DW statistic. For example the Breusch-Godfrey tests for serial correlation or the Serial Correlation LM test. Unfortunately such tests are not available for panel data estimation (Eviews 7 User's Guide:26,155).

[14] Other autocorrelation tests are not available for panel equations, consequently a manual attempt is made to detect AR(1) serial correlation using the 'Wooldridge test (2002)'.[14] Wooldridge's method uses residual from a regression in first differences. The residuals from the first differenced equation are regressed on the lagged residuals to obtain an estimator of the coefficient of autocorrelation ρ. Under the null hypothesis that the original idiosyncratic errors are uncorrelated, the residual from this equation should have an autocorrelation coefficient of -0.5. Unfortunately, the unbalanced and uneven spacing of observations generates invalid results for ρ.

[15] It is noted that the White period method can also be employed. Both were tried and yielded similar results, though the White Cross section method did yield marginally better results.

[16] Typically there may be some scale effect in cross sectional data, whereas in time series data, the variables tend to be of similar orders of magnitude (Gujarati 2006:392).

[17] For details see Wooldridge 2003 at pp. 266-267.

[18]The formula for the calculated F statistic is F=(R/k)/ ((1-R)/ (n-k-1); where k is the number of independent variables and n is the number of observations (Wooldridge 2003:266). Meanwhile, the critical F value has (approximately) an $F_{k,\ n-k-1}$ distribution under the null hypothesis of homoskedasticity. (Wooldridge 2003:266).

[19] The formula for the calculated LM statistic for heteroskedasticity is simply the sample size times the R-squared from Equation (5): LM = n x R. (Wooldridge 2003:266). Meanwhile, under the null hypothesis, critical LM value is distributed asymptotically as $\chi^2_{k.}$

[20] Moreover, a problem arises in testing for heteroskedasticity given that any serial correlation will generally invalidate such tests (Wooldridge 2003:414) and it is unclear whether correcting the standard errors for autocorrelation is sufficient to validate tests of heteroskedasticity.

[21] This is plausible given that the data set is 'short and wide', consisting of many more cross sectional units than time period observations. Given the cross sectional units are countries which are of varying sizes, controlling for heteroskedastictity seems necessary and desirable.

[22] Low income countries are those with \$935 or less 2007 GNI per capita; lower middle income refer to those with \$936 - \$3 705 2007 GNI per capita while upper middle income constitutes those with \$3 706 - \$ 11 455 GNI per capita.[22].

[23] The traditional areas in Latin America's agrarian structure follows a common pattern in which a small number of latifundios control a large proportion of the agricultural land while a vast number of minifundios must scratch out an existence on a meagre fraction of the occupied land. According to the FAO, 1.3% of landowners in Latin America hold 71.6% of the land under cultivation (Todaro 2009:442).

[24] E.g. greater openness, macroeconomic stability and favourable industrial and labour market policies

[25] The use of dummy variables in additive form enables a distinction to be made between the intercept coefficients of the two groups while the use of dummy variables in the interactive or multiplicative form enables differentiation between slope coefficients of the groups (Gujarati 2006:307).

[26][26] A plausible explanation for this is that because the determinants of distribution lie in the structural features of the economy which change only slowly – for example ownership and social relations (Besley and Burgess 2003: 11); distribution itself changes relatively little over time.

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