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# Estimating the Relative Benefits of Agricultural Growth on the Distribution of Expenditures

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**Summary.** — Does the sectoral composition of aggregate economic growth affect poverty? We ask whether agricultural growth in developing countries increases the expenditures of poorer households more than growth in other sectors. While some reduced form analyses have tackled this question using either country-level time series data, regional panel data for one country, or cross-sectional country data, this paper is unusual in using panel data for many countries. We improve on much of the existing literature by devising an instrumental variables strategy to correct for the endogeneity of sectoral GDP growth, involving averaging over sectoral income growth rates for neighboring countries. Our principal finding from our instrumental variable estimator is that the estimated elasticities associated with growth in agricultural income are significantly greater than for non-agricultural income for all but the extreme top and bottom deciles. In the middle range of the income distribution the effect of a given GDP growth due to agriculture is 3–4 times larger than if it was due to non-agricultural activities. Having established that on average growth in GDP originating in agriculture is more beneficial for poorer deciles, we finally explore whether this is a pattern which holds across different groupings of countries. A second important finding is that there is heterogeneity across some groupings. Most particularly, we find that it is the poorest people in the poorest countries for whom agricultural income growth is the most beneficial.


*Key words* — agricultural growth, distribution of expenditures, unbalanced panel dataset, global development

## 1. INTRODUCTION

While aggregate growth in an economy may improve the welfare of both wealthy and poor households, the latter are most usually rural, and rural households have employment and incomes that depend disproportionately on agriculture. It is natural to wonder if growth in aggregate agricultural income has a different effect on the welfare of poorer households than does growth elsewhere in the economy. The question is an important one for many policy issues. Faced with continuing extensive poverty, many development agencies and scholars have suggested the need to refocus growth on agriculture (Bill & Melinda Gates Foundation, 2011; World Bank, 2007), arguing that the alternatives of redistributing income generated outside of agriculture or migration out of agriculture to urban areas are difficult to achieve and create other problems.

Of course, we are not the first to wonder whether growth in agriculture may be more effective than growth in the rest of the economy in reducing poverty; an extensive theoretical and empirical literature already exists on the subject which we discuss in Section 2. The theoretical literature focuses on the different transmission mechanisms of an exogenous gain in agricultural productivity on poverty, while the empirical literature analyzes the reduced form relationship, and generally documents a stronger association between poverty reduction and growth originating in agriculture compared to growth originating in non-agriculture, with the exception of Latin American countries.

In this paper we tackle this question by comparing changes in the level and distribution of household expenditures due to growth in both aggregate agricultural and aggregate non-agricultural incomes. We use growth in household expenditures as the outcome of interest because we believe expenditures to be the best available indicator of material well-being; also, these are the data generally used for poverty calculations for most low-income countries. However, our analysis differs from most other studies in several aspects. First, we consider growth in expenditures across the entire distribution rather than the simple poverty headcount ratio, giving a richer picture of the effect of sectoral growth on welfare. Second, we use the deciles as defined within each country, rather than a common international benchmark of expenditures. To correct the underlying assumption that deciles of very different countries have similar relationship with agriculture, we then pursue some heterogeneity analysis. Finally, we tackle the issue of simultaneity between sectoral income and expenditures using an instrumental variable approach, allowing us to take a stand on the causality of sectoral growth on welfare.

The simple regression we would like to estimate relates expenditure growth for differently positioned households to growth in sectoral income, the latter weighted by its share in total aggregate income; this is described in Section 4. The question of whether the poor benefit more from agricultural income growth than growth in other sectors could then be answered simply by examining the relative size of the coefficients on aggregate income growth from agriculture and from other sectors.

In practice, there is a series of challenges we must face before estimating such a regression. First, we do not have household level data that would allow us to make comparisons across countries. Instead, we use data from the World Bank's PovcalNet project and consider estimates of household

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expenditures from different expenditure deciles; in effect we construct a panel of ten representative "households" for each country, each representing an expenditure decile. [1] We discuss these data in Section 3(a).

Second, the resulting "panel" is extremely unbalanced, since the underlying expenditure surveys are conducted at irregular intervals. This creates some important accounting issues when we turn to estimation, treated in Section 4(a).

Third, some countries, some years, and perhaps some deciles can naturally be expected to have different expenditure growth rates for reasons unrelated to sectoral income growth. A global financial shock may cause expenditure growth to slow for everyone; households' risk attitudes or time preferences may imply different rates of expenditure growth across deciles (Lawrance, 1991); the endowments of a particular country or some aspect of the structure of its economy may imply systematically different rates of expenditure or income growth even over long periods; and variation in the global price of agricultural commodities will change the composition of income across sectors for many countries. We attempt to deal with these kinds of alternative sources of variation in expenditure and income growth in a fairly agnostic manner, using fixed effects and related methods for dealing with what Wooldridge (2002) calls "unobserved effects." So: we account for aggregate cross-country shocks using a collection of time effects; and for systematically different rates of expenditure growth across the distribution we use a set of decile fixed effects. We would be inclined to also use a complete set of country fixed effects to deal with differences in endowments, but with these we reach the limits of our dataset; instead we employ a set of continent fixed effects, which in practice seems to be effective.

Fourth, the stochastic process governing country-level agricultural income exhibits more time-series variance than does income from other sectors. From the point of view of our exercise, this greater variance produces an attenuation "bias" in the resulting estimates of the connection between agricultural income and welfare, since we are interested not in the short-run effect of things like weather shocks on expenditures but on the longer-run effects of things like improvements in agricultural productivity. We are also concerned about the related issue of endogeneity; even the simplest general equilibrium models with investment imply simultaneity in the determination of income and expenditures. We address these issues using a simple instrumental variables strategy, using averages of *neighboring* countries' sectoral income growth as instruments for own-income growth (see Section 4(b)).

Fifth, even after controlling for time, continent, and decile fixed effects in growth, we are concerned that there may be heterogeneity across countries in the way agricultural income growth affects households in different parts of the expenditure distribution. We explore this possible heterogeneity by interacting various fixed or pre-determined country characteristics with income growth from different sectors, reporting those results in Section 5(d).

We summarize our main results. First, poorer households' expenditures grow more in response to growth from agriculture than do the expenditures of wealthier households, and this holds across all deciles. We call this result *monotonicity*, and it is both very robust and important. Monotonicity also holds for growth from non-agricultural sources, but in the opposite direction, with wealthier households' expenditures responding more than poorer households'. Second, it is not just across deciles that we see an effect: within poorer deciles, households benefit significantly more from growth in agriculture than they do from growth in other sectors. Third and finally, the connection between expenditures and sectoral income growth is importantly and significantly different across different groups of countries. In particular, it is the poorest households in the poorer *countries* for whom agricultural income growth is most important.

## 2. THEORY AND EMPIRICAL EVIDENCE

From a theoretical standpoint, a long tradition of dual economy models that aggregate the economy into two sectors—agriculture and non-agriculture—has served to identify the transmission mechanisms of an exogenous agricultural productivity increase on welfare (Johnston & Mellor, 1961). Transmission mechanisms include employment, food prices, real wages, and the demand for non-tradable goods produced in the rural non-farm economy.

The tradition in the dual economy literature is to assume that consumption expenditures are equal to real income and that labor income is the source of expenditures while capital income is saved and invested. An increase in growth in one sector would affect the welfare of only the part of the population actually employed in that sector. If expenditures are distributed differently across households in the two sectors, then an increase in employment in one sector will have an effect on the aggregate distribution of expenditures. If, for example, households employed in the agricultural sector tend to be poorer, an increase in agricultural employment will have an equalizing effect on the entire distribution of expenditures (Thorbecke & Jung, 1996).

For a country with a closed economy (or simply high costs to trade), an increase in agricultural productivity induces a decrease in food prices. All consumers benefit from lower food prices, but most particularly the poor, who typically spend a larger share of their income on food (Mellor, 1978). If there is surplus labor and wages are tied to the cost of living to secure a fixed real subsistence wage, lower food prices can induce a decrease in the nominal wage, fostering employment and growth in the non-agricultural sector (Lele & Mellor, 1981).

When workers are mobile and wages are equated across sectors, differences in the rate of growth of different sectors can result in changes in the distribution of expenditures through the employment effect. For example, Loayza and Raddatz (2010) formulate a model in which expenditures of the poor are equal to the prevailing wage, while non-poor households can borrow or lend to smooth away the effects of variation in labor income on expenditures (alternatively, one could assume that the non-poor are the owners of the economy's capital stock). The model shows that the effects of sectoral growth on real wages are larger for sectors with larger employment and a lower elasticity of demand for labor, namely agriculture and services.

Another strand of literature is based on a three-sector aggregation of the economy, with a non-tradable sector in addition to the agricultural and, say, manufacturing sectors. A key determinant of the overall effect of an initial growth impetus in agriculture is the linkages created in fostering demand for the non-tradable sector products (Haggblade, Hammer, & Hazell, 1991). To the extent that labor is not fully mobile, then in addition to asymmetric effects on the functional sources of income any growth that originates in the rural economy stands to have a more direct impact on the rural population, where many of the poor live.

Much of the empirical support to the claim that agricultural growth is good for aggregate growth, employment, and wel-

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fare is based on simulation models that rely on demand and supply elasticities that are not estimated (see for example Haggblade *et al.*, 1991). Thorbecke and Jung (1996) use social accounting with postulated elasticities applied to Indonesia, thus finding that agriculture and services contribute more to poverty reduction that the industrial sectors.

Within-country or within-region studies arguably offer the best evidence we have on the connection between aggregate agricultural income growth and household welfare, perhaps because in these contexts one can construct a proper panel dataset. In an important series of papers Datt and Ravallion (Datt & Ravallion, 1998a, 1998b; Ravallion & Datt, 1996) use panel data for states in India and show a systematic and relatively uniform association between agricultural growth and poverty reduction, but a very heterogeneous relationship between non-agricultural growth and poverty change. With province-level panel data for China over the period 1985–96, Fan, Chan-Kang, and Mukherjee (2005) find that agricultural growth is associated with a reduction of rural poverty while non-agricultural growth is associated with an increase in rural poverty. With provincial data for 1983–2001, Montalvo and Ravallion (2010) show that the primary sector was the driving force behind the spectacular decrease in poverty in China. Suryahadi, Suryadarma, and Sumarto (2009) conduct an exercise similar to that of Ravallion and Datt (1996) but for Indonesia, and are able to distinguish between the rural and urban poor. They find that growth in services is good for both the rural and urban poor, with the effects of agricultural growth focused more specifically on the rural poor. In a similar spirit, Warr (2006) uses national data from four Asian countries (Thailand, Indonesia, Malaysia, and the Philippines) from the 1960s to 1999 in a panel analysis and finds similar results, in that growth in agriculture and services were associated with a decrease in poverty, with the estimated coefficient on agriculture substantially smaller than the coefficient on services, and the coefficient on manufacturing not significantly different from 0. Looking at the 25 countries with the greatest success at reducing extreme poverty under the period of the Millennium Development Goals, Cervantes-Godoy and Dewbre (2010) find that while economic growth was a key determinant, growth in agricultural income was especially important. Bresciani and Valdes (2007) provide evidence of the role of agricultural growth on poverty reduction through rural labor markets, farm income, food prices, and economy-wide multipliers in different country case studies.

Other studies have resorted more systematically to cross-sectional country-level time series data, thus looking for average effects across a large set of countries and hence economic structures. Using data from 80 countries spanning 1980–2002, Christiaensen, Demery, and Kulh (2011) find a stronger association between overall poverty decrease and growth originating in agriculture (an elasticity they call "participation") than growth originating in either of the other two sectors. With higher participation, slower growth of agriculture may still deliver more poverty reduction than the growth of non-agriculture. In contrast, using a slightly different method, Bravo-Ortega and Lederman (2005) find that in Latin America, it is the non-agricultural sector that has the strongest effect in reducing poverty. Focusing on the role of the unskilled labor market, Loayza and Raddatz (2010) find evidence that growth in income from sectors with high unskilled labor shares has a disproportionate effect in reducing poverty rates. In a somewhat different specification, Dollar, Kleineberg, and Kraay (2016) regress growth rates in income of the poorest 20% on growth in average income and on changes in the share of agriculture in GDP. The significance of the coefficient on the agricultural variable suggests that, even controlling for aggregate growth, faster growth in agriculture is likely to disproportionately benefit the poor.

There is also a literature that challenges the dominant role of agricultural growth for poverty reduction. Lanjouw, Murgai, and Stern (2013) for example argue that it is the non-agricultural sector in the rural areas that is both more dynamic and more pro-poor, and hence the most important contributor to poverty reduction in rural India. Collier and Dercon (2014) note that productivity in agriculture, and especially in the smallholder sector, is so low that economic development and poverty alleviation in Africa will have to come from a radical transformation of the agricultural sector and massive exodus from agriculture. They also cite works on the role of migration in the reduction of poverty in rural areas. Most of the literature that cautions against the importance given to agriculture for poverty alleviation however relates to a different argument: while the relatively strong poverty impact of agricultural growth seems to be a fairly robust result, the cost of investing to obtain a given growth is far higher in agriculture than in other sectors, making it an inefficient instrument for growth and welfare (Dercon & Gollin, 2014). Our paper does not address this issue at all, but aims at contributing to the literature on the sectoral growth–poverty linkage.

An issue in almost all of the studies we have discussed is simultaneity between sectoral growth and the welfare indicator used in the analysis. A contribution of this paper is to tackle this issue using an instrumental variable approach to try to measure the effect of an exogenous increase in sectoral growth on welfare. We use the same database collected by the World Bank as do other cross-country analyses, although we only select the countries for which welfare is measured by consumption expenditures.[2] We also use data on all deciles, rather than only on e.g., poverty rates, as in Christiaensen *et al.* (2011) and other studies described above.

When using cross-country evidence on changes in the distribution of income or expenditures one has to make an early choice regarding whether it is better to consider the distribution of these welfare measures *within* countries or *across* countries. The former choice leads to an empirical strategy that groups together different welfare quantiles across countries, so that for example, one imagines that the poorest 10 percent of households in Tanzania are similarly positioned to the poorest 10 percent of households in China, despite the substantial differences in the level of real expenditures of the quantile across these two countries. The latter choice construes distribution as a global phenomenon, with the result that the poorest 10 percent of all households globally may all be located in a very small number of countries. If what we want to measure is the *global* distribution of welfare one also logically ought to weight countries by their populations in any cross-country analysis.

Different researchers have made different choices.[3] In this paper we take the country-focused approach, and analyze the relationship between welfare and sectoral growth of all deciles of the distribution *within* countries, rather than on a measure of poverty level or distribution *across* countries.[4]

## 3. DATA

We use data from two main sources. The World Bank's online PovcalNet project[5] provides data on the levels and distributions of expenditures for selected countries and years, while data on aggregate income from different countries'

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national income and product accounts is compiled in the World Development Indicator (WDI) database. Additional data on various country characteristics that we use are also from the WDI unless indicated otherwise.[6] We discuss data on both expenditures and income below.

### (a) *Expenditure data*

Over the last several decades, the World Bank has accumulated a large number of datasets from a large number of developing countries which are based on household-level surveys, statistically representative of the populations of those countries, and which include data on non-durable goods expenditures. Though the micro-data from these surveys are not generally available, the World Bank provides data on aggregate expenditures by decile for many of these countries. Our sample is restricted to the countries and years for which we have information on expenditures data for at least three points in time (two differences). The sample covers 62 countries, with variable numbers of observations over 1978–2011, totaling 310 surveys.

This sample of countries and years is not a random sample of the countries of the world. Instead, it is a sample of countries where household expenditure surveys have been conducted (perhaps under the auspices of the World Bank). It has however a large coverage, including 81% of the population in low- and middle-income countries in 2000. In terms of continents, the sample includes 97% of the population of South Asia, 70% of Sub-Saharan Africa, and 20% of Latin America and Caribbean.[7] There is no clear bias in this sampling of developing countries except for the obvious and egregious absence of all but one Latin American countries. We are thus reasonably confident that the analysis given here can be applied to all developing countries save those in Latin America.

A third of the countries in our data have a first survey before 1990 while information starts in the 1990s for the other countries. Some statistics are given in Table 1. The lowest three expenditure deciles garner on average 12% of aggregate expenditures, while the highest three deciles enjoy 57% (with more than 30% for the highest decile). The average expenditure ratio of the highest to lowest group is 5.12. On average, the lowest income deciles have seen their income grow at a faster rate (3.2% annually) than the upper three deciles (2.7%), and the ratio of highest to lowest expenditures has fallen by .05 per year. This average however hides heterogeneity, with an increase in inequality in 24 of the countries, notably China, Rwanda, Macedonia, and South Africa.

Table 2 documents in more details the expenditure growth rates of the different deciles for several groups of countries that we will consider later in the analysis, i.e., by continent, literacy level, poverty level, and inequality. The table exhibits two important facts about expenditure growth in our sample of countries. The first is that every group has positive average real expenditure growth. The second is that poorer deciles' expenditures grow more quickly than wealthier deciles. The monotonicity of expenditure growth seems to be a quite robust feature of these data.

### (b) *Sectoral income data*

Corresponding to this period of observation, we have annual measures of agricultural, non-agricultural, and aggregate incomes. Table 1 shows an average annual growth of real GDP per capita of 3.5%,[8] with a sharp contrast between a dynamic non-agricultural sector (with average growth rate of 4.2%) and the agricultural sector which on average was stagnant. Note however a large standard deviation that reveals large heterogeneity across countries. Fig. 1 plots average annual growth rates of agriculture against growth rates outside of agriculture for the countries in our sample over the period 1980–2011. Overall, the growth in these two sectors of the economy are correlated, though not surprisingly the agricultural sector grows at a slower rate almost everywhere. There is however great heterogeneity in terms of both growth level and disparity between the sectors across countries. In the upper right corner of the graph, China, Cambodia, and Vietnam exhibit sustained high growth rates exceeding 6% annually in non-agriculture and 2–4% in agriculture over 30 years. Very low agricultural performance is seen in Russia and Eastern-European countries during this period of transition. Several African countries are below the fitted line (Central African Republic, Zambia, Burkina Faso, Guinea, Guinea-Bissau, and Morocco) meaning that the performance of their agriculture sector relative to the rest of the economy was better than average.

Table 1. *Expenditures in the year closest to 2000 for each country; annual growth over the years of observation for each country, from survey data for expenditures and from annual data for sectoral growth*

| | Mean | Std. Dev. |
|---|---|---|
| Panel A—Expenditures | | |
| Share of total expenditures (%) | | |
| Lowest decile | 2.9 | 0.7 |
| Highest decile | 30.3 | 5.4 |
| Deciles 1–3 | 11.9 | 2.4 |
| Deciles 8–10 | 57.1 | 5.3 |
| Ratio deciles 8–10/1–3 | 5.12 | 1.86 |
| Average annual growth rate in expenditures/capita | | |
| Deciles 1–3 | 0.032 | 0.030 |
| Deciles 8–10 | 0.027 | 0.030 |
| Annual change in ratio 8–10/1–3 | −0.047 | 0.178 |
| Panel B—Income | | |
| GDP/capita in 2000 USD | 5301 | 4379 |
| Average share of agriculture | 0.24 | 0.14 |
| In Africa | 0.31 | 0.16 |
| In Asia | 0.30 | 0.12 |
| In other continents | 0.18 | 0.11 |
| Average annual growth rates in value-added | | |
| Aggregate GDP/capita | 0.035 | 0.029 |
| Agriculture | 0.004 | 0.025 |
| Non-agriculture | 0.042 | 0.032 |

## 4. METHODS

Index the set of countries in our dataset by $\ell = 1, 2, \ldots, L$, and index time by $t \in \{1, 2, \ldots, T\} = \mathbb{T}$. Let $q$ index expenditure quantiles (deciles in this application). The value of expenditures for quantile $q$ in country $\ell$ at time $t$ is denoted by $c_t^{(\ell,q)}$.

Suppose that total income $y_{\ell t}$ of country $\ell$ at time $t$ is derived from two sectors, so that

$$y_{\ell t} = y^1_{\ell t} + y^2_{\ell t}.$$

Then, since changes in logarithms approximate growth rates, we have

$$\Delta \log y_{\ell t} \approx \theta^1_{\ell t-1} \Delta \log y^1_{\ell t} + \theta^2_{\ell t-1} \Delta \log y^2_{\ell t}, \tag{1}$$

where $\theta^1_{\ell t-1}$ and $\theta^2_{\ell t-1}$ represent the shares of agricultural and non-agricultural sectors in GDP in year $t-1$ respectively.

Table 2. *Average annual real expenditure growth rates by expenditure decile (in columns). Each panel reports average growth rates conditioning on, respectively, the continent, the initial adult literacy rate, the poverty rate, and the Gini coefficient. These last three are "high" or "low" relative to the median. In between panels we report the centered $R^2$ statistic associated with the regressions reported above. Standard errors are computed using the estimator described by Stock and Watson (2008)*

| Obs. 310 | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% | 100% |
|---|---|---|---|---|---|---|---|---|---|---|
| | 2.91*** | 2.63*** | 2.51*** | 2.42*** | 2.36*** | 2.30*** | 2.25*** | 2.20*** | 2.16*** | 1.98*** |
| | (0.74) | (0.60) | (0.54) | (0.52) | (0.51) | (0.50) | (0.50) | (0.51) | (0.53) | (0.64) |
| $R^2$ | 0.04 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.04 | 0.02 |
| Africa | 2.76*** | 2.32*** | 2.12*** | 1.99*** | 1.88*** | 1.79*** | 1.72*** | 1.66*** | 1.60*** | 1.38* |
| | (1.03) | (0.79) | (0.68) | (0.62) | (0.58) | (0.56) | (0.55) | (0.56) | (0.58) | (0.72) |
| Asia | 2.65*** | 2.57*** | 2.50*** | 2.43*** | 2.39*** | 2.35*** | 2.31** | 2.26** | 2.20** | 1.95 |
| | (0.99) | (0.84) | (0.85) | (0.86) | (0.88) | (0.91) | (0.94) | (0.98) | (1.04) | (1.32) |
| Other | 3.67 | 3.48* | 3.44* | 3.43* | 3.43* | 3.42* | 3.41* | 3.41* | 3.42* | 3.44 |
| | (2.28) | (2.08) | (2.05) | (2.04) | (2.04) | (2.04) | (2.05) | (2.05) | (2.07) | (2.24) |
| $R^2$ | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.02 |
| Higher literacy | 2.83*** | 2.49*** | 2.33*** | 2.20*** | 2.10*** | 2.00*** | 1.90*** | 1.81*** | 1.70*** | 1.30** |
| | (0.84) | (0.64) | (0.56) | (0.51) | (0.49) | (0.47) | (0.47) | (0.48) | (0.50) | (0.61) |
| Lower literacy | 3.06** | 2.91** | 2.85** | 2.84** | 2.85** | 2.88** | 2.91** | 2.96** | 3.03** | 3.26** |
| | (1.53) | (1.35) | (1.32) | (1.31) | (1.31) | (1.32) | (1.33) | (1.34) | (1.38) | (1.65) |
| $R^2$ | 0.04 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.04 | 0.04 | 0.04 | 0.03 |
| More poor | 2.75** | 2.60** | 2.49** | 2.42** | 2.38** | 2.34** | 2.31** | 2.29** | 2.29* | 2.27* |
| | (1.22) | (1.08) | (1.06) | (1.06) | (1.07) | (1.09) | (1.11) | (1.13) | (1.18) | (1.36) |
| Less poor | 3.03*** | 2.66*** | 2.52*** | 2.42*** | 2.34*** | 2.27*** | 2.20*** | 2.13*** | 2.06*** | 1.75*** |
| | (0.94) | (0.71) | (0.62) | (0.57) | (0.54) | (0.52) | (0.51) | (0.51) | (0.53) | (0.67) |
| $R^2$ | 0.04 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.04 | 0.04 | 0.02 |
| Less equal | 3.71*** | 3.27*** | 3.06*** | 2.91*** | 2.80*** | 2.70*** | 2.62*** | 2.53*** | 2.43*** | 1.90** |
| | (0.96) | (0.76) | (0.73) | (0.73) | (0.74) | (0.75) | (0.76) | (0.77) | (0.79) | (0.91) |
| More equal | 2.16* | 2.04** | 1.99** | 1.96*** | 1.94*** | 1.92*** | 1.90*** | 1.90*** | 1.90*** | 2.04** |
| | (1.12) | (0.91) | (0.81) | (0.75) | (0.71) | (0.69) | (0.68) | (0.68) | (0.72) | (0.90) |
| $R^2$ | 0.04 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.04 | 0.02 |

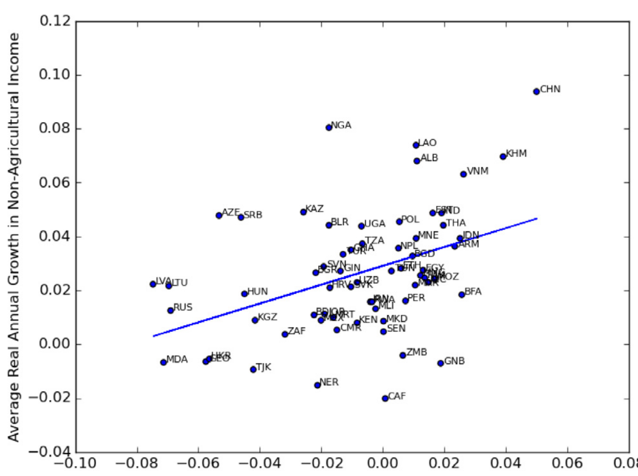


Fig. 1. *Average annual growth in real income from non-agricultural sources versus agricultural sources over the period 1980–2011.*

This decomposition of aggregate income growth then motivates the estimating equation

$$\Delta \log c_t^{(\ell,q)} = \alpha^q + \sum_{s=1}^{2} \beta_q^s \theta_{\ell t-1}^s \Delta \log y_{\ell t}^s + \eta_t + \epsilon_t^{(\ell,q)}. \tag{2}$$

Here the terms $\{\alpha^q\}$ are quantile "fixed effects" which capture variation in differences in the expected trend of log expenditures across quantiles, but not across time or countries.[9]

The terms $\beta_q^1 \theta_{\ell t-1}^1 \Delta \log y_{\ell t}^1$ and $\beta_q^2 \theta_{\ell t-1}^2 \Delta \log y_{\ell t}^2$ capture, respectively, the average effect of growth in total income from the agricultural and non-agricultural sectors on the growth of expenditures of quantile $q$. The time fixed effects $\eta_t$ account for the variation across time that is common to all countries and deciles, related, for example, to changes in the international prices of agricultural commodities or interest rates, or to technological changes. The disturbance term $\epsilon_t^{(\ell,q)}$ captures the influence of unobservables on expenditure growth.

In (2) the parameters $\beta_q^s$ represent the elasticity of expenditures of decile $q$ with respect to aggregate growth originating from sector $s$ (analogous to what Christiaensen *et al.*, 2011 call the *participation* effect of income growth on poverty). These parameters indicate the relative effects of the sectors, controlling for their size.

## (a) *Accounting for an unbalanced panel*

The panel we are working with for this problem is quite unbalanced. It is unbalanced not only because we have data on expenditures in different country-quantiles over variable periods of time, but also because the intervals *between* periods in which we have data are variable.

When one wishes to estimate an equation such as (2) using an unbalanced panel, the first difficulty one encounters is simply dealing with the fact that one cannot always observe the first differences $\Delta \log c_t^{(\ell,q)}$, since any given country $\ell$ with data at $t$ won't necessarily also have data in an adjacent period—we observe expenditures for a given country $\ell$ only in periods

$\mathbb{T}_\ell = \{t_1^\ell,\ t_2^\ell, \ldots, t_{T_\ell}^\ell\}$ which is a subset of all the periods we could hope to have data for, $\mathbb{T}$.

An example may help. Suppose that we are interested in evaluating (2) for country $\ell$ at $t_2^\ell$, and that the previous year of observation $t_1^\ell$ is three periods earlier, so that $t_2^\ell - t_1^\ell = 3$.

Let $\Delta^d$ denote the $d$-difference operator: for any sequence $\{x_t\}$ we define the operator by $\Delta^d x_t = x_t - x_{t-d}$. In our example, we cannot calculate $\Delta \log c_{t_2^\ell}^{(\ell,q)}$, but we *can* calculate $\Delta^{t_2^\ell - t_1^\ell} \log c_{t_2^\ell}^{(\ell,q)}$.

Now, how can we relate this third difference to the quantities we are actually interested in measuring? It is easy to see that we have

$$\Delta^{t_j^\ell - t_{j-1}^\ell} \log c_{t_j^\ell}^{(\ell,q)} \equiv \sum_{r=t_{j-1}^\ell+1}^{t_j^\ell} \Delta \log c_r^{(\ell,q)}. \tag{3}$$

Using this identity along with (2) then allows us to construct an estimable expression in which a variable difference appears on the left-hand side:

$$\Delta^{t_j^\ell - t_{j-1}^\ell} \log c_{t_j^\ell}^{(\ell,q)} = (t_j^\ell - t_{j-1}^\ell)\alpha^q + \sum_{s=1}^{2} \beta_q^s \theta_{\ell t_{j-1}^\ell}^s \Delta^{t_j^\ell - t_{j-1}^\ell} \log y_{\ell t_j^\ell}^s + \sum_{r=t_{j-1}^\ell+1}^{t_j^\ell} \eta_r + \sum_{r=t_{j-1}^\ell+1}^{t_j^\ell} \epsilon_r^{(\ell,q)}. \tag{4}$$

Each term directly corresponds to a similar term in (2). The left-hand term is a variable difference, the variation depending on the years in which data are available for a particular country. The "fixed effect" $\alpha^q$, which governs quantile-specific growth trends must now be scaled by the number of years in the difference $t_j^\ell - t_{j-1}^\ell$. The year-time effects will involve a sum of several of these, since typically several years will pass between observations for a given country $\ell$. The terms involving income growth (both agricultural and non-agricultural) have also changed from first differences to variable differences. And finally, the disturbance term will typically be a sequence of year-specific disturbance terms summed up to capture all the effects of unobservables over the period between observations.

### (b) *Measurement error and endogeneity*

Agricultural income is notable for its volatility. This is particularly true for crop income that depends on erratic weather. Agricultural income is also difficult to measure and to constrain to fit the concept of a calendar year. Fig. 2 illustrates the point using data from Morocco. A similar pattern is observed in most of our sample countries: The average standard deviation of annual growth rates over the period 1980–2011 is 7.2% for non-agricultural income and 11.1% for agricultural income. Except for six countries, all have standard deviations of non-agricultural growth rates less than 10%. In contrast, half the countries have standard deviations above 10% for agriculture. This suggests that the value recorded as annual agricultural income is likely a poor approximation of the permanent income from the agricultural sector, or its *de facto* contribution to the welfare of the population in any given year. Taking growth rates over several years between two surveys in our specification does not do much to attenuate this concern, as these remain subject to the hazard of the specific values at the end points. This creates a phenomenon akin to

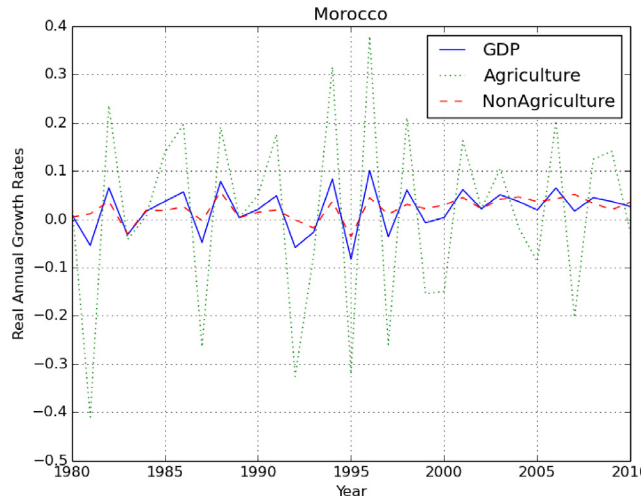


Fig. 2. *Illustration using Morocco.*

measurement errors, with attenuation bias on the estimated coefficients as a consequence.

A second concern relates to the possible endogeneity of sectoral growth. Unobserved shocks which influence either the level or the distribution of expenditures within a country may also influence aggregate sources of income. Examples (depending on the model) might include movement of the real exchange rate or of the interest rate, price controls, or subsidy schemes.

To deal with these two problems of measurement error and potential endogeneity, we adopt a simple instrumental variables' strategy. We use the mean of *neighboring* countries' growth rates of sectoral income as an instrument for own sectoral income growth, a strategy similar to one employed (in a household context) by Gertler and Molyneaux (2000). The idea is that many of the unobserved shocks which might simultaneously influence income and expenditures will be country-specific, while at least some of the shocks which influence sectoral productivity (e.g., weather-related shocks for agriculture) are likely to be correlated across neighboring countries.[10]

These first stage regressions for the (weighted) sectoral growth rate of country $\ell$ between years $t_{j-1}^\ell$ and $t_j^\ell$ is:

$$\theta_{\ell t_{j-1}^\ell}^s \Delta \log y_{\ell t_j^\ell}^s = \gamma^s \theta_{-\ell t_{j-1}^\ell}^s \Delta \log y_{-\ell t_j^\ell}^s + \sum_{r=t_{j-1}^\ell+1}^{t_j^\ell} \eta_r + v_{t_j^\ell}^{s,\ell} \qquad s = 1, 2; \tag{5}$$

where $\theta_{-\ell t_{j-1}^\ell}^s \Delta \log y_{-\ell t_j^\ell}^s$ represents the average sectoral growth in neighboring countries between years $t_{j-1}^\ell$ and $t_j^\ell$ (weighted by those countries' lagged shares). The sectoral value-added data necessary for the construction of the instruments are available from the World Development Indicator database for all relevant countries and all years. For example, the instrument for Mexico sectoral growth during 1996–98 is the weighted average of the sectoral growth between 1996 and 1998 of its three neighboring countries, USA, Guatemala, and Belize, regardless of whether these countries and years are among the countries and years for which we observe expenditures per deciles.[11]

Estimates of the $\gamma^s$ parameters are reported in Table 3. The two columns are for the agricultural income and non-agricultural income, respectively. The rows each employ a dif-

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Table 3. *"First stage" regressions of the growth rate of sectoral income on the average of neighboring countries' growth rates of sectoral income. Labels in first column indicate the unobserved effects strategy for the regression*

| | Agriculture | | | Non-agriculture | | |
|---|---|---|---|---|---|---|
| | Coeff. | Std. Err | $R^2$ | Coeff. | Std. Err | $R^2$ |
| Constant | 0.360 | 0.061 | 0.101 | 0.608 | 0.050 | 0.321 |
| Continent FE | 0.351 | 0.066 | 0.108 | 0.341 | 0.064 | 0.403 |
| Year FE | 0.333 | 0.064 | 0.180 | 0.393 | 0.066 | 0.434 |
| Continent & year FE | 0.295 | 0.069 | 0.192 | 0.188 | 0.072 | 0.505 |

ferent unobserved effects strategy, starting with just a constant (or, more precisely the time elapsed between rounds, as in the first term of (4)); then substituting a set of continent dummies; then a set of year effects (added up, also as in (4)); then finally combining both year and continent effects.

Coefficients are fairly precisely estimated, and significant. The *F*-statistic associated with a test of the null hypothesis that both coefficients are zero comfortably exceeds the Staiger and Stock (1997) rule-of-thumb value of 10 in every case, indicating that weak instruments are not a problem. However, the table also reveals something about our instruments.

For the agriculture regressions, coefficients and standard errors are fairly insensitive to the unobserved effects strategy we employ, with coefficient estimates ranging from 0.360 to 0.295. $R^2$ statistics for the agriculture regressions do change, but only importantly when we add year effects—the addition of continent fixed effects has only a very modest impact on the fit of the regressions. This is an indication that there is important time-series variation in agricultural income growth common to all countries, rather than being peculiar to neighbors' average growth rates.

For the non-agricultural regressions we see a different pattern. Coefficients respond strongly to the addition of continent dummies, and modestly to the addition of year effects. With the full set of continent and year dummies the *t*-statistic on neighbors' average growth of non-agriculture income falls to a value less than three—large enough to reject zero, but if we were *only* instrumenting for non-agricultural income implying an *F*-statistic below the Staiger–Stock rule of thumb. This is not what we do, of course, but this first stage regression hints that our instrumental variables estimator may be relatively imprecise. [12]

## 5. RESULTS

The central finding of this paper is that across countries, growth in GDP from agriculture has a larger effect on the expenditures of the poor than does growth in GDP from other sectors. In this section we make this point using a series of different tools. We first present a simple graphical analysis, then proceed with OLS and IV estimations.

Having established that on average growth in GDP originating in agriculture is more beneficial for poorer deciles, we finally explore whether this is a pattern which holds across different groupings of countries.

### (a) *Graphical results*

To illustrate the point that we will make more rigorously in what follows, in Fig. 3 we plot the difference in expenditure growth between the three lowest and three highest deciles against the difference in sectoral growth. The sectoral growth rates are each estimated over the period of observation for the expenditures.

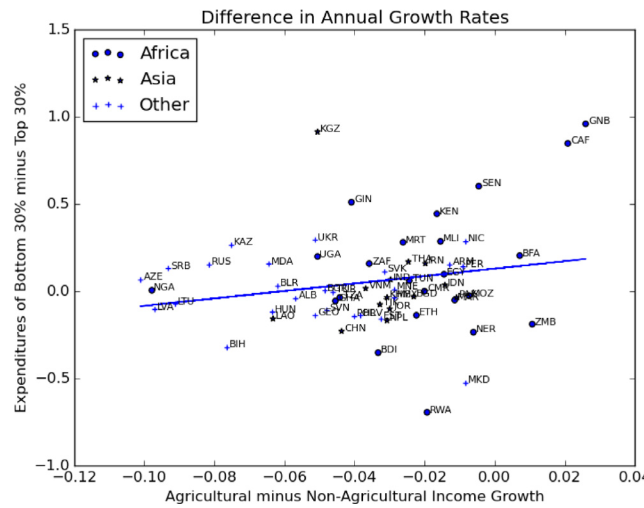


Fig. 3. *Differences in growth rates in expenditures versus differences in growth rates for agricultural and non-agricultural income.*

We observe a positive correlation between a relatively higher growth in agriculture and higher growth in expenditures for the poorest deciles. However, there is also considerable heterogeneity in the distribution of expenditures even for a given difference in sectoral growth.

The different points on the scatterplot of Fig. 3 have different markers depending on whether the country is in Africa, Asia, or some "Other" continent. Very informally one can see that these three continental groupings seem to have different behavior. Most of the countries of Asia are clustered near the center of the figure, showing a relatively 'balanced' growth process, with small differences between both agricultural and non-agricultural sources of growth and also small differences in expenditure growth rates across deciles. In contrast, a group of mostly Eastern European countries have much larger growth rates in income outside of agriculture but relatively equal rates of expenditure growth, creating a cluster in the left-hand side of the figure. All African countries, but Nigeria, are found much farther to the right, where the relative rate of agricultural income growth is higher. An 'eye-ball' regression just using the African countries suggests a much higher correlation; this is an issue we return to below.

### (b) *Ordinary least squares with unobserved effects*

As a first attempt at estimating (4), we follow the lead given by the empirical studies mentioned in Section 2 and simply use Ordinary Least Squares (OLS) to compute point estimates of the elasticities $\beta_q^s$, controlling for time and continent effects. Time fixed effects accommodate aggregate shocks to expenditures or sectoral sources of income; Continent fixed effects help

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account for the clustering by continents observed in Fig. 3 that might otherwise lead to biased estimates. To compute the standard errors of these point estimates we adapt a procedure described by Stock and Watson (2008), which permits arbitrary forms of heteroskedasticity and correlation across quantiles (Stock and Watson's method is designed for balanced panels).

OLS results are reported in Table 4. None of the coefficients associated with growth in agricultural income is significant; and neither for agriculture do we observe a strict pattern of monotonically declining coefficients across deciles that we observed in our discussion of expenditure growth. Further, in no case are estimated agricultural coefficients significantly different from the non-agricultural coefficients *within* a decile, owing perhaps to our relatively imprecise estimates of the agriculture coefficients. However, income derived from non-agricultural sources is statistically significant for every decile above the first, and does increase monotonically across deciles.

The coefficients have an interpretation as share-weighted elasticities. For example, Table 4 suggests that on average a one-percentage-point increase in GDP due to non-agricultural income growth is associated with approximately a half-percentage-point increase in the growth rate of expenditures, with higher values for higher deciles and lower values for lower deciles. This would indicate a regressive effect on the distribution of expenditures.

The results in Table 4 are estimated using a set of decile, year, and continent effects, but with this estimator and specification these are not of great importance. Estimating the same equation but with only a constant or only continent dummies results in coefficient estimates which are somewhat larger in magnitude, but with no appreciable difference in precision and only a modest improvement in fit.

### (c) *Instrumental variables with unobserved effects*

We next turn to the instrumental variable estimator described above to deal with measurement errors in agricultural growth and to address some possible forms of endogeneity in both agricultural and non-agricultural income growth.

Results using this instrumental variables' estimator appear in Table 5. The first thing to notice is that for agriculture the pattern of monotonicity described earlier survives in this specification, with coefficients for agricultural growth decreasing across deciles.

The second thing to notice is that coefficients for agriculture and non-agriculture are significantly different at conventional levels (see the rows of Table 5 with the $\chi^2$ statistics), with $p$-values less than 0.10 for the bottom six deciles. This is the chief evidence supporting our general finding that growth originating in different sectors has different effects on households in different parts of the expenditure distribution. Re-estimating this relationship with different unobserved effects strategies yields results that are slightly weaker but broadly consistent—in any event a joint test of the equality of coefficients across sectors for all deciles leads to a rejection of the null hypothesis of equality.

The third thing to notice is that while growth from agriculture has a positive and significant (at the 10% level of confidence) effect on expenditure growth for the bottom five deciles, growth from other sectors is never significant. One cannot reject the null hypothesis that no decile benefits from non-agricultural sources of GDP growth.[13] Point estimates associated with growth from non-agricultural sectors are in fact negative for the bottom two deciles, but little should be made of this fact, both because none of these coefficients are significant and because even if significant these negative coefficients would only be an indication that non-agricultural income growth reduced expenditure growth relative to the positive mean levels reported in Table 2, not that it actually makes it negative.

Taken together these results suggest a progressive effect of income growth originating in agriculture: a one-percentage-point increase in GDP due to agricultural income growth is associated with a 5.6-percentage-point increase in the growth rate of expenditures of the bottom decile, declining to 3.9 per-

Table 4. *Expenditure growth by decile and sectoral income regressed on share-weighted sectoral incomes. The $\chi^2$ statistics test the hypothesis that coefficients are equal across sectors. Point estimates from OLS. Using year and continent fixed effects.*

| Obs. 310 | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% | 100% |
|---|---|---|---|---|---|---|---|---|---|---|
| $\theta\Delta$ log Agriculture | 1.11 | 0.69 | 0.52 | 0.43 | 0.38 | 0.37 | 0.35 | 0.36 | 0.36 | 0.54 |
| | (0.97) | (0.76) | (0.69) | (0.66) | (0.65) | (0.65) | (0.65) | (0.66) | (0.68) | (0.81) |
| $\theta\Delta$ log NonAgriculture | 0.23 | 0.38** | 0.47*** | 0.52*** | 0.56*** | 0.59*** | 0.62*** | 0.65*** | 0.68*** | 0.76*** |
| | (0.24) | (0.19) | (0.17) | (0.17) | (0.17) | (0.16) | (0.17) | (0.17) | (0.17) | (0.21) |
| Decile | −0.04 | −0.04 | −0.03 | −0.03 | −0.03 | −0.03 | −0.03 | −0.03 | −0.03 | −0.02 |
| | (0.03) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| $\chi^2$ | 0.8 | 0.2 | 0.0 | 0.0 | 0.1 | 0.1 | 0.1 | 0.2 | 0.2 | 0.1 |
| $p$-Value | (0.378) | (0.691) | (0.946) | (0.893) | (0.801) | (0.748) | (0.708) | (0.691) | (0.667) | (0.794) |

Table 5. *Instrumental variables results. Expenditure growth by decile and sectoral income regressed on share-weighted sectoral incomes. The $\chi^2$ statistics test the hypothesis that coefficients are equal across sectors. Using year and continent fixed effects.*

| Obs. 310 | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% | 100% |
|---|---|---|---|---|---|---|---|---|---|---|
| $\theta\Delta$ log Agriculture | 5.65* | 4.68* | 4.45* | 4.19* | 3.93* | 3.65* | 3.35* | 3.00 | 2.54 | 0.12 |
| | (3.13) | (2.53) | (2.32) | (2.19) | (2.09) | (2.00) | (1.93) | (1.88) | (1.86) | (2.25) |
| $\theta\Delta$ log NonAgriculture | −0.12 | -0.06 | 0.03 | 0.09 | 0.14 | 0.18 | 0.22 | 0.26 | 0.32 | 0.42 |
| | (0.54) | (0.43) | (0.40) | (0.38) | (0.36) | (0.35) | (0.35) | (0.35) | (0.36) | (0.47) |
| Decile | −0.03 | −0.04 | −0.04 | −0.04 | −0.04 | −0.04 | −0.04 | −0.04 | −0.04 | −0.04 |
| | (0.03) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| $\chi^2$ | 3.4 | 3.6 | 3.7 | 3.6 | 3.4 | 3.1 | 2.7 | 2.2 | 1.5 | 0.0 |
| $p$-Value | (0.066) | (0.059) | (0.055) | (0.058) | (0.065) | (0.078) | (0.100) | (0.141) | (0.228) | (0.895) |

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centage points for the fifth decile, and with no effect at all on the highest decile.

Note the differences between our instrumental variables and OLS results. Estimated coefficients associated with agriculture are much higher in Table 5, suggesting that the OLS coefficients were attenuated by measurement error, in line with our discussion above in Section 4(b) At the same time coefficients associated with non-agricultural income growth are lower (though not significantly so) and have considerably higher standard errors than in the OLS case.

The results we have which seem quite robust are (i) monotonicity of the effects of agricultural income growth across deciles, indicating a certain progressivity in the effects of agricultural income on the distribution of expenditures; and (ii) significantly different effects from income originating in different sectors.

### (d) *Heterogeneity*

We next turn our attention to the question of whether the effects of income growth from different sectors on expenditures differ across countries. We are interested in particular in whether there is heterogeneity across different particular observable groups. We might expect such heterogeneity to stem from differences in endowments or social conditions across countries. We consider four ways of dividing countries: the initial level of poverty; the initial level of inequality; the initial level of adult literacy; [14] and conclude with the contrast across continents, which of course may capture many differences in endowments and social structures. [15,16]

#### (i) *Initial poverty*

Our work so far addresses the question of how income growth from agriculture affects the distribution of expenditures within countries, rather than across them. We are now able to say something about the effects of such growth on the *global* distribution of welfare by asking whether the effects of income growth from agriculture on distribution are different for poorer and wealthier countries within our sample.

We group countries by initial level of (headcount) poverty rates and report results in Table 6. In our sample, the median poverty rate across countries is 15.27%, ranging from a minimum of 0.04% in Bosnia and Herzogovina to 81.32% in Burundi. [17] Because we are interested in whether there is heterogeneity in elasticities across the *global* ranking of poverty rates, not the ranking within continents, we produce these results without the extra continent dummies that we have used in most of the analysis above.

There are several things worthy of note in Table 6. First, one can reject the null hypothesis that there is no heterogeneity by country poverty level. Specifically, one can reject the hypotheses that coefficients are equal across poorer and wealthier countries in the bottom three deciles (the first row of $\chi^2$ statistics).

Second, the robust pattern of monotonicity observed elsewhere for the coefficients associated with agriculture is preserved for poor countries, but the direction is nearly *reversed* for wealthy countries. Thus, the progressive effect of agricultural income growth on distribution seems to be confined to the poorer half of the countries in our sample.

Third, we can reject the hypothesis that agricultural and non-agricultural coefficients are equal within the poorer half of countries (the second row of $\chi^2$ statistics) for the bottom six deciles, in line with the baseline results of Table 5. However, we *cannot* reject equality among the richer half of countries. This is additional evidence that the progressive effect of agricultural income growth on the welfare of the poor may be confined to the poor in the poorest countries.

Our findings here are related to results found by other authors. For example, Christiaensen *et al.* (2011) finds that agriculture growth matters most for poverty reduction when using the poverty line of \$1 per capita rather that \$2 per capita. Though our results are not directly comparable (because we use expenditures rather than poverty status as our dependent variable), in our analysis the income level of the deciles nevertheless directly measures the intensity of poverty, since lower deciles in poorer countries are typically poorer than lower deciles in richer countries.

All of the three notable findings discussed above turn out to also be true when we look at poverty across countries within a continent, by estimating (4) while including continent dummies. However, in this specification the addition of extra controls causes the significance of the individual coefficients seen in Table 6 to disappear. Thus, though income growth from agriculture affects the expenditure distribution differently in poor and wealthy countries, the fact that with the addition of continent effects the individual significance vanishes suggests that the *continent* (beyond the proportion of poor coun-

Table 6. *Interactions between sectoral income variables and whether (initial) poverty rate is above or below the median. Using year fixed effects.*

| Obs. 310 | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% | 100% |
|---|---|---|---|---|---|---|---|---|---|---|
| Poorer × $\theta\Delta$ log Agriculture | 7.98*** | 5.95** | 5.31** | 4.77** | 4.28** | 3.80** | 3.30** | 2.76* | 2.05 | −2.01 |
| | (3.04) | (2.47) | (2.22) | (2.04) | (1.87) | (1.71) | (1.57) | (1.43) | (1.32) | (1.67) |
| Poorer × $\theta\Delta$ log NonAgriculture | −1.80 | −1.43 | −1.15 | −0.97 | −0.81 | −0.67 | −0.53 | −0.39 | −0.22 | 0.33 |
| | (1.31) | (1.08) | (1.01) | (0.97) | (0.93) | (0.91) | (0.89) | (0.88) | (0.89) | (1.09) |
| Wealthier × $\theta\Delta$ log Agriculture | 5.63 | 7.39 | 7.91 | 8.12 | 8.16 | 8.15 | 8.11 | 8.02 | 7.88 | 9.87 |
| | (16.12) | (14.92) | (15.20) | (15.53) | (15.77) | (15.98) | (16.17) | (16.37) | (16.63) | (19.41) |
| Wealthier × $\theta\Delta$ log NonAgriculture | −0.37 | −0.27 | −0.14 | −0.07 | −0.01 | 0.05 | 0.11 | 0.16 | 0.24 | 0.40 |
| | (0.69) | (0.57) | (0.53) | (0.50) | (0.48) | (0.46) | (0.45) | (0.44) | (0.44) | (0.54) |
| Decile | −0.06 | −0.06 | −0.06 | −0.06 | −0.06 | −0.06 | −0.06 | −0.05 | −0.05 | −0.04 |
| | (0.03) | (0.03) | (0.03) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) |
| $\chi^2$ | 8.0 | 6.7 | 6.2 | 5.8 | 5.3 | 4.7 | 4.0 | 3.1 | 1.7 | 2.8 |
| *p*-Value | (0.018) | (0.035) | (0.044) | (0.055) | (0.071) | (0.094) | (0.136) | (0.217) | (0.431) | (0.247) |
| $\chi^2$ (Equal among "Poorer") | 7.6 | 6.5 | 6.1 | 5.6 | 5.1 | 4.4 | 3.7 | 2.8 | 1.6 | 1.1 |
| *p*-Value | (0.006) | (0.010) | (0.014) | (0.018) | (0.024) | (0.035) | (0.055) | (0.095) | (0.211) | (0.300) |
| $\chi^2$ (Equal among "Wealthier") | 0.1 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.2 | 0.2 | 0.2 | 0.2 |
| *p*-Value | (0.715) | (0.613) | (0.601) | (0.602) | (0.609) | (0.616) | (0.624) | (0.635) | (0.649) | (0.629) |

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tries in the continent) may matter in understanding these patterns, a question we return to below.

(ii) *Initial Inequality*

One interpretation of the results of last section is that it is not really *poorer* countries, but *less equal* countries to which this applies, and we only find our earlier results because less equal countries also tend to be countries with more poor. This certainly is not a new idea: Datt and Ravallion (1998), Ravallion (2007), Suryahadi *et al.* (2009), and Christiaensen *et al.* (2011) all argue for the possible importance of initial inequality in understanding the effects of aggregate sectoral income growth on poverty.

We do not really have the data to distinguish between these two hypotheses adequately, but we can at least divide countries according to initial inequality and see what happens. We divide countries into groups depending on whether their initial Gini coefficient is above or below the median. Results from this exercise are reported in Table 7.

In contrast with our poverty results, dividing countries by initial inequality preserves our earlier monotonicity results for both more and less unequal countries, with agriculture tending to differentially benefit poorer households in both groups. However, we can no longer reject the hypothesis that coefficients are the *same* across groups, whether we include continent fixed effects or not, leading us to conclude that initial inequality may be a less salient dimension of heterogeneity across countries than is initial poverty.

(iii) *Literacy*

Datt and Ravallion (1998), Ravallion and Datt (2002), and Suryahadi *et al.* (2009) all pay attention to the possible role of literacy in explaining the effects of sectoral income growth on household welfare; the idea is that it may not be poverty *per se* that affects households' responses to sectoral productivity shocks, but the effects of these shocks on the marginal product of human capital. Accordingly, in Table 8 countries are grouped by whether the rate of adult literacy is above or below the median. Results are consistent with the view that literacy matters: In countries with low literacy rates, agricultural growth plays a very progressive role in fostering expenditures of lower deciles, with sharply declining elasticities from 6.7 to −3.2. In contrast, in high-literacy countries, elasticities are *increasing* from 4.1 to 6.7 (though these are not significant).

Table 7. *Interactions between sectoral income variables and whether (initial) Gini coefficient is above or below the median. Using year fixed effects.*

| Obs. 310 | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% | 100% |
|---|---|---|---|---|---|---|---|---|---|---|
| Less equal × $\theta\Delta$ log Agriculture | 6.02* | 5.08* | 4.78** | 4.43** | 4.08** | 3.73** | 3.33** | 2.87* | 2.22 | −0.61 |
| | (3.29) | (2.71) | (2.42) | (2.19) | (1.99) | (1.81) | (1.64) | (1.48) | (1.36) | (1.59) |
| Less equal × $\theta\Delta$ log NonAgriculture | −0.47 | −0.40 | −0.26 | −0.18 | −0.11 | −0.05 | 0.01 | 0.08 | 0.15 | 0.33 |
| | (0.99) | (0.77) | (0.72) | (0.68) | (0.66) | (0.65) | (0.65) | (0.66) | (0.70) | (0.98) |
| More equal × $\theta\Delta$ log Agriculture | 3.61 | 2.65 | 2.74 | 2.73 | 2.69 | 2.61 | 2.55 | 2.47 | 2.39 | 0.99 |
| | (5.01) | (4.04) | (3.93) | (3.91) | (3.93) | (3.96) | (4.01) | (4.10) | (4.26) | (5.18) |
| More equal × $\theta\Delta$ log NonAgriculture | 0.05 | 0.11 | 0.18 | 0.21 | 0.24 | 0.26 | 0.28 | 0.29 | 0.31 | 0.31 |
| | (0.51) | (0.40) | (0.38) | (0.36) | (0.35) | (0.35) | (0.35) | (0.35) | (0.35) | (0.43) |
| Decile | −0.04 | −0.04 | −0.04 | −0.04 | −0.04 | −0.05 | −0.05 | −0.05 | −0.04 | −0.04 |
| | (0.03) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| $\chi^2$ | 4.0 | 4.3 | 4.6 | 4.6 | 4.5 | 4.3 | 3.8 | 3.1 | 1.9 | 0.3 |
| *p*-value | (0.133) | (0.115) | (0.102) | (0.101) | (0.106) | (0.118) | (0.149) | (0.215) | (0.395) | (0.859) |
| $\chi^2$ (Equal among "Less equal") | 4.0 | 4.3 | 4.5 | 4.6 | 4.5 | 4.3 | 3.8 | 3.1 | 1.8 | 0.2 |
| *p*-Value | (0.047) | (0.039) | (0.034) | (0.033) | (0.035) | (0.039) | (0.051) | (0.080) | (0.175) | (0.617) |
| $\chi^2$ (Equal among "More equal") | 0.5 | 0.4 | 0.4 | 0.4 | 0.4 | 0.3 | 0.3 | 0.3 | 0.2 | 0.0 |
| *p*-Value | (0.483) | (0.533) | (0.520) | (0.529) | (0.542) | (0.564) | (0.583) | (0.607) | (0.636) | (0.899) |

Table 8. *Interactions between sectoral income variables and whether (initial) adult literacy rate is above or below the median. Using year fixed effects.*

| Obs. 310 | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% | 100% |
|---|---|---|---|---|---|---|---|---|---|---|
| High Literacy × $\theta\Delta$ log Agriculture | 4.10 | 4.85 | 5.29 | 5.54 | 5.65 | 5.73 | 5.80 | 5.85 | 5.94 | 6.68 |
| | (6.08) | (5.24) | (5.29) | (5.43) | (5.57) | (5.70) | (5.84) | (5.98) | (6.19) | (7.19) |
| High Literacy × $\theta\Delta$ log NonAgriculture | −0.23 | −0.14 | −0.03 | 0.04 | 0.09 | 0.13 | 0.18 | 0.22 | 0.28 | 0.41 |
| | (0.58) | (0.45) | (0.41) | (0.39) | (0.38) | (0.37) | (0.36) | (0.37) | (0.38) | (0.55) |
| Low Literacy × $\theta\Delta$ log Agriculture | 6.74** | 4.83* | 4.21* | 3.68* | 3.21* | 2.74* | 2.24 | 1.68 | 0.93 | −3.17* |
| | (3.11) | (2.48) | (2.22) | (2.00) | (1.82) | (1.64) | (1.49) | (1.34) | (1.24) | (1.75) |
| Low Literacy × $\theta\Delta$ log NonAgriculture | −0.86 | −0.66 | −0.45 | −0.35 | −0.28 | −0.22 | −0.17 | −0.12 | −0.04 | 0.18 |
| | (1.16) | (0.92) | (0.85) | (0.81) | (0.79) | (0.78) | (0.78) | (0.80) | (0.85) | (1.27) |
| Decile | −0.05 | −0.05 | −0.05 | −0.05 | −0.05 | −0.05 | −0.05 | −0.05 | −0.05 | −0.04 |
| | (0.03) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) |
| $\chi^2$ | 5.3 | 4.8 | 4.6 | 4.4 | 4.0 | 3.6 | 3.0 | 2.2 | 1.2 | 3.6 |
| *p*-Value | (0.069) | (0.089) | (0.098) | (0.113) | (0.132) | (0.165) | (0.222) | (0.328) | (0.536) | (0.164) |
| $\chi^2$ (Equal among "High Literacy") | 0.5 | 0.9 | 1.0 | 1.0 | 1.0 | 1.0 | 0.9 | 0.9 | 0.9 | 0.8 |
| *p*-Value | (0.474) | (0.336) | (0.310) | (0.307) | (0.313) | (0.321) | (0.330) | (0.342) | (0.355) | (0.378) |
| $\chi^2$ (Equal among "Low Literacy") | 5.2 | 4.3 | 3.9 | 3.5 | 3.2 | 2.8 | 2.2 | 1.4 | 0.5 | 2.6 |
| *p*-Value | (0.023) | (0.039) | (0.049) | (0.060) | (0.073) | (0.095) | (0.138) | (0.230) | (0.497) | (0.105) |

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Table 9. *Interactions between sectoral income variables and continents. Using year fixed effects. Average Spearman correlation coefficient of error correction terms across deciles (Kendall's $\mathscr{W}$) is 0.660.*

| Obs. 310 | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% | 100% |
|---|---|---|---|---|---|---|---|---|---|---|
| AF × $\theta\Delta$ log Agriculture | 7.31 | 4.07 | 3.29 | 2.71 | 2.28 | 1.88 | 1.53 | 1.20 | 0.76 | −2.71 |
| | (5.53) | (4.98) | (4.47) | (4.13) | (3.79) | (3.49) | (3.16) | (2.83) | (2.49) | (2.55) |
| AF × $\theta\Delta$ log NonAgriculture | −7.93 | −7.93 | −7.17 | −6.63 | −6.04 | −5.49 | −4.82 | −4.07 | −3.15 | −1.06 |
| | (8.27) | (7.49) | (6.68) | (6.17) | (5.67) | (5.25) | (4.79) | (4.34) | (3.90) | (4.18) |
| AS × $\theta\Delta$ log Agriculture | −13.86 | −11.55 | −8.96 | −7.37 | −5.89 | −4.67 | −3.31 | −1.91 | −0.28 | 2.34 |
| | (18.29) | (16.57) | (14.82) | (13.76) | (12.75) | (11.93) | (11.05) | (10.24) | (9.54) | (10.88) |
| AS × $\theta\Delta$ log NonAgriculture | −2.29 | −2.39 | −2.22 | −2.10 | −1.96 | −1.82 | −1.65 | −1.44 | −1.19 | −0.58 |
| | (3.40) | (3.06) | (2.72) | (2.52) | (2.32) | (2.16) | (1.98) | (1.81) | (1.64) | (1.66) |
| Other × $\theta\Delta$ log Agriculture | 9.05 | 5.78 | 4.65 | 3.97 | 3.37 | 2.88 | 2.47 | 2.06 | 1.64 | 1.15 |
| | (17.48) | (15.55) | (14.36) | (13.60) | (12.82) | (12.13) | (11.44) | (10.72) | (9.96) | (8.63) |
| Other × $\theta\Delta$ log NonAgriculture | −2.08 | −2.14 | −1.88 | −1.70 | −1.51 | −1.33 | −1.11 | −0.87 | −0.58 | 0.08 |
| | (2.42) | (2.19) | (1.95) | (1.81) | (1.66) | (1.54) | (1.40) | (1.27) | (1.14) | (1.21) |
| Decile | −0.17 | −0.18 | −0.17 | −0.16 | −0.15 | −0.14 | −0.13 | −0.12 | −0.10 | −0.06 |
| | (0.05) | (0.04) | (0.04) | (0.04) | (0.03) | (0.03) | (0.03) | (0.03) | (0.02) | (0.02) |
| $\chi^2$ | 9.1 | 6.6 | 6.2 | 5.8 | 5.4 | 4.9 | 4.4 | 3.8 | 2.7 | 0.3 |
| *p*-Value | (0.028) | (0.085) | (0.101) | (0.124) | (0.146) | (0.178) | (0.219) | (0.284) | (0.435) | (0.950) |
| $\chi^2$ (Equal among "AF") | 8.2 | 6.0 | 5.6 | 5.1 | 4.7 | 4.3 | 3.8 | 3.2 | 2.1 | 0.3 |
| *p*-Value | (0.004) | (0.014) | (0.018) | (0.024) | (0.030) | (0.039) | (0.052) | (0.075) | (0.144) | (0.567) |
| $\chi^2$ (Equal among "AS") | 0.5 | 0.4 | 0.2 | 0.2 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.1 |
| *p*-Value | (0.492) | (0.548) | (0.621) | (0.678) | (0.739) | (0.798) | (0.872) | (0.961) | (0.920) | (0.781) |
| $\chi^2$ (Equal among "Other") | 0.4 | 0.3 | 0.2 | 0.2 | 0.2 | 0.1 | 0.1 | 0.1 | 0.1 | 0.0 |
| *p*-Value | (0.515) | (0.602) | (0.642) | (0.670) | (0.698) | (0.724) | (0.750) | (0.781) | (0.820) | (0.898) |

Because the results are perhaps slightly stronger in Table 6 we have a slight preference for the hypothesis that poverty plays a key role rather than literacy, but this contrast of course should not be interpreted as causal. Adult literacy rates and the poverty level are fairly highly (negatively) correlated, with a Spearman correlation coefficient of −0.71; we really have no good way to distinguish between the importance of a country being poor or a country having a high rate of adult literacy using these data.

(iv) *Continents*

We finally turn to a broader classification, dividing countries by continents (Africa, Asia, and "Other"). We are interested in exploring whether these different geographical groupings have different responses to growth from different sectors, as Fig. 3 seemed to hint.

We reject the hypothesis that coefficients are the same across continental groupings (the first row of $\chi^2$ statistics in Table 9) for the first three deciles, confirming the hypothesis generated by Fig. 3. Recalling that much of the variation in that figure seemed to be due to African countries, we confirm in Table 9 that *only* African countries have significantly different coefficients across sectors, just as only poorer countries exhibit significant differences in Table 6; the Spearman correlation coefficient between initial country poverty and "Africa" is 0.59. Monotonicity is preserved in Africa and Asia, but fails in the "Other" continent.

## 6. CONCLUSION

We have explored some different approaches toward estimating the effects of agricultural growth on expenditure growth and distribution. Our basic approach takes advantage of the fact that we have data on both aggregate rates of expenditure growth across countries, and on changes in the distribution of these expenditures across households.

We improve on much of the existing literature by exploiting the additional information available in the distribution of expenditures beyond poverty status, but also in using instrumental variables techniques to deal with problems of measurement error and endogeneity. Our instruments are constructed by averaging over sectoral income growth rates for neighboring countries. We also take advantage of the panel aspect of these data, a task which is complicated by the extremely unbalanced nature of the panel.

We find first that income growth from agriculture has a progressive effect on the distribution of expenditures; this seems a very robust feature of the data, that survives nearly all our experiments. We also find that the sectoral composition of income matters—coefficients on income from agriculture and income from other sectors are significantly different for the lower deciles.

Finally, we explore the possibility of heterogeneity across countries, experimenting with dividing countries according to their initial poverty rates, their initial (Gini) inequality, their initial rates of adult literacy, and simply dividing them by continents. Several of these groupings are fairly highly correlated, making it impossible (with these data) to say that one grouping is 'right' while the others are wrong. But dividing the data by initial poverty, initial literacy, and continent all lead to a rejection of the hypothesis of groups having the same response, so that there does indeed seem to be important heterogeneity. Our preferred division and strongest results involve initial poverty—we draw the conclusion that income growth from agriculture is disproportionately beneficial for the poorest households in the poorer countries.

This last result suggests that the strong poverty reduction impact of agricultural growth is likely to weaken as development progresses. This is plausibly because the poor population will be less located in rural areas and working in agriculture and will instead reside in urban areas (reducing the direct effects of agriculture) and that food markets will be more integrated in the world economy (reducing the food price channel). The drivers of poverty reduction will then have to be found in the labor intensive sectors and in the cities. Our study however suggests that this is not yet the case for the poorer countries of the world.

## NOTES

1. If households are very mobile then some fraction of these may move across deciles; this poses a challenge our data do not equip us to face.

2. This is because the distribution of income and expenditures across the population can be quite different (Milanovic, 2006), and theory strongly suggests that the *response* of expenditures and income to changes in sectoral productivity may be very different (Deaton, 1992).

3. For example, Bravo-Ortega and Lederman (2005) take a country-focused approach, while Christiaensen *et al.*, 2011 use a global approach (though without weighting countries by population).

4. This is because population-weighted analysis of the global distribution of welfare over the recent decades would be dominated by the changes in distribution in just two large countries with rapid growth, India and China, for which we already have analyses (Ravallion & Datt, 1996, Ravallion & Chen, 2007).

5. http://iresearch.worldbank.org/PovcalNet; downloaded 2014.

6. http://data.worldbank.org/data-catalog/world-development-indicators; downloaded 2014.

7. The sample includes 57% of the population of the low-income countries (the large missing countries are the Democratic Republic of Congo, the Democratic Republic of Korea, Afghanistan, and Madagascar), 87% of the lower middle-income countries, 80% of the upper middle-income countries, 58% of the high-income non-OECD countries and only 6% of the high-income OECD countries. The large missing countries of Sub-Saharan Africa are the Democratic Republic of Congo, Sudan, Cote d'Ivoire, Madagascar, and Angola. For most of Latin American countries, PovCalNet reports aggregate data by deciles of income rather than expenditures.

8. Data on GDP and sectoral value added are taken from the World Development Indicators database, as is the GDP deflators we use to obtain "real" measures of income and expenditures. Note that because we work with growth rates the base year of the deflator (which varies across countries) is immaterial, and there's no need to use PPP or other conversions.

9. Making quantile effects invariant over time is justifiable if different quantiles within a country can be treated as representative households. If many households move across deciles this could cause trouble, but this kind of mobility is beyond our ability to deal with using these data.

10. At the suggestion of referees, we've also experimented with using a Hodrick–Prescott filter to extract the 'trend' from our agriculture variable. This procedure does not result in significant differences in our estimated coefficients.

11. Consistency of our estimator requires that the error term $\epsilon_t^{(\ell,q)}$ be orthogonal to the instruments, conditional on the time and quantile fixed effects. But if measurement errors in sectoral income growth are correlated across neighboring countries, or if the process which determines growth in deciles' expenditures also plays a role in determining neighboring countries' aggregate sectoral incomes then our estimator will not be consistent. It is not clear how to test for either of these possible problems; however, the assumptions required for consistency of our estimator are weaker than what is typically assumed elsewhere in the cross-country literature.

12. In our search for good instruments, we have also considered rainfall, smoothed series, and various lags. In some cases we cannot reject the null hypothesis that coefficients are unchanged (rainfall, lagged neighbors' averages). In other cases the addition of the alternative instrument to our basic set allows a test of overidentifying restrictions, which we reject (lagged own growth).

13. Loayza and Raddatz (2010) argue that sectors which are intensive in unskilled labor (agriculture, manufacturing, and construction) reduce poverty more than other sectors (services, mining, and utilities). We have experimented with a three-sector specification (agriculture, industry, and services; the best our data allow), and found (i) that this has no significant effect on our estimates of the coefficients associated with growth from agriculture; and (ii) that we are generally unable to reject the null hypothesis that coefficients on industry and services are equal to each other.

14. All these are "initial" values because we want to only introduce interaction variables that are pre-determined. What we actually use, of course, is the initial year a country appears in our dataset.

15. Datt and Ravallion (1998), Ravallion and Datt (2002), and Byerlee, Diao, and Jackson (2005) all suggest that inequality in land endowments may be another important determinant of the effects of aggregate agricultural growth on the poor. However, unfortunately we do not have cross-country data which would allow us to measure landlessness or inequality in land-holdings. Experiments with different measures of arable land did not reveal interesting differences, but none of these measures captured inequality or landlessness.

16. In principle, one could extend this exploration of heterogeneity by allowing for higher orders of interaction—perhaps the effects of agricultural income growth on expenditure growth are different across poor countries which have high and low levels of literacy, for example. But in practice the limitations of our dataset do not allow us to draw such fine distinctions.

17. Poverty rate is here defined by the share of the population with a consumption per capita of less that $1.25 per day in 2000 Purchasing Power Parity US dollars.

## REFERENCES


Bill & Melinda Gates Foundation (2011). *Agriculture development strategy overview*. Bill & Melinda Gates Foundation.

Bravo-Ortega, C., & Lederman, D. (2005). *Agriculture and national welfare around the world: Causality and international heterogeneity since 1960*. Washington, DC: World Bank Policy Research Working Paper Series 3499.

Bresciani, F., & Valdes, A. (2007). *Beyond food production: The role of agriculture in poverty reduction*. Rome: FAO.

Byerlee, D., Diao, X., & Jackson, C. (2005). *Agriculture, development, and pro-poor growth: Country experiences in the post-reform era*, Agriculture and rural development discussion paper 21. Washington, DC: World Bank.

Cervantes-Godoy, D., & Dewbre, J. (2010). *Economic importance of agriculture for poverty reduction*, Food, agriculture, and fisheries working papers 23. OECD.

Christiaensen, L., Demery, L., & Kulh, J. (2011). The (evolving) role of agriculture in poverty reduction—an empirical perspective. *Journal of Development Economics, 96*(2), 239–254.

Collier, P., & Dercon, S. (2014). African agriculture in 50 years: Smallholders in a rapidly changing world?. *World Development, 63*, 92–101.

Datt, G., & Ravallion, M. (1998a). Farm productivity and rural poverty in India. *Journal of Development Studies, 34*(4), 62–85.

Datt, G., & Ravallion, M. (1998b). Why have some Indian states done better than others in reducing rural poverty?. *Economica, 65*(257), 17–38.

Deaton, A. (1992). *Understanding consumption*. Oxford: Clarendon Press.

Dercon, S., & Gollin, D. (2014). Agriculture in African development: Theories and strategies. *Annual Review of Resource Economics, 6*(1), 471–492.

Dollar, D., Kleineberg, T., & Kraay, A. (2016). Growth still is good for the poor. *European Economic Review, 81*(1), 68–85.

Fan, S., Chan-Kang, C., & Mukherjee, A. (2005). *Rural and urban dynamic and poverty: Evidence from China and India*. Washington, DC: International Food Research Institute, FCND Discussion Paper 196.

Gertler, P. J., & Molyneaux, J. W. (2000). The allocation and impact of planning program inputs in Indonesia. *Population Development Review, 26*(Suppl.), 61–88.

Haggblade, S., Hammer, J., & Hazell, P. B. R. (1991). Modeling agricultural growth multipliers. *American Journal of Agricultural Economics, 73*, 361–374.

Johnston, B. F., & Mellor, J. W. (1961). The role of agriculture in economic development. *The American Economic Review, 51*(4), 566–593.

Lanjouw, P., Murgai, R., & Stern, N. (2013). Nonfarm diversification, poverty, economic mobility, and income inequality: a case study in village India. *Agricultural Economics, 44*(4–5), 461–473.

Lawrance, E. C. (1991). Poverty and the rate of time preference: Evidence from panel data. *Journal of Political Economy, 99*(1), 54–77.

Lele, U. J., & Mellor, J. W. (1981). Technological change, distribution bias and labor transfer in a two-sector economy. *Oxford Economic Papers, 33*, 426–441.

Loayza, N., & Raddatz, C. (2010). The composition of growth matters for poverty alleviation. *Journal of Development Economics, 93*(1), 137–151.

Mellor, J. W. (1978). Food price policy and income distribution in low-income countries. *Economic Development and Cultural Change, 27*, 1–26.

Milanovic, B. (2006). Global income inequality: A review. *World Economics, 7*(1), 131–157.

Montalvo, J., & Ravallion, M. (2010). The pattern of growth and poverty reduction in China. *Journal of Comparative Economics, 38*, 2–16.

Ravallion, M. (2007). Inequality is bad for the poor. In J. Micklewright, & S. Jenkins (Eds.), *Inequality and poverty re-examined*. Oxford: Oxford University Press.

Ravallion, M., & Chen, S. (2007). China's (Uneven) progress against poverty. *Journal of Development Economics, 82*(1), 1–42.

Ravallion, M., & Datt, G. (1996). How important to India's poor is the sectoral composition of economic growth?. *The World Bank Economic Review, 10*(1), 1–25.

Ravallion, M., & Datt, G. (2002). Why has economic growth been more pro-poor in some states of India than others?. *Journal of Development Economics, 68*(2), 381–400.

Staiger, D., & Stock, J. (1997). Instrumental variables regression with weak instruments. *Econometrica, 65*, 557–586.

Stock, J. H., & Watson, M. W. (2008). Heteroskedasticity-robust standard errors for fixed effects panel regression. *Econometrica, 76*(1), 155–174.

Suryahadi, A., Suryadarma, D., & Sumarto, S. (2009). The effect of location and sectoral components of economic growth on poverty: Evidence from Indonesia. *Journal of Development Economics, 89*, 109–117.

Thorbecke, E., & Jung, H.-S. (1996). A multiplier decomposition method to analyze poverty alleviation. *Journal of Development Economics, 48*(2), 279–300.

Warr, P. G. (2006). Poverty and growth in Southeast Asia. *ASEAN Economic Bulletin, 23*(3), 279–302.

Wooldridge, J. (2002). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.

World Bank (2007). *World development report 2008: Agriculture for development*. Washington, DC: World Bank.




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