Are The Poverty Effects of Trade Policies Invisible?

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Abstract

With the advent of the WTO's Doha Development Agenda, as well as the Millennium Development Goals aiming to reduce poverty by 50 percent by 2015, poverty impacts of trade reforms have attracted increasing attention. This has been particularly true of agricultural trade reform due to the importance of food in the diets of the poor, relatively higher protection in agriculture, as well as the heavy concentration of global poverty in rural areas where agriculture is the main source of income. Yet some in this debate have argued that, given the extreme volatility in agricultural commodity markets, the additional price and poverty impacts due to trade liberalization might well be undetectable. This paper formally tests this "*invisibility hypothesis*" via stochastic simulation of a computable general equilibrium framework. The hypothesis test is based on the comparison of two sets of price and poverty distributions. The first originates solely from the inherent variability in global staple grains markets, while the second combines the effects of this inherent variability and trade reform. Results indicate that the short-run impacts of trade liberalization on poverty are not distinguishable from market volatility in majority of the fifteen focus countries – suggesting that the poverty impacts of agricultural trade liberalization may indeed be invisible.

JEL classification: C68, F17, I32, Q17, R20

Keywords: Trade policy reform, agricultural trade, computable general equilibrium, developing countries, poverty headcount, volatility, stochastic simulation, non-parametric hypothesis testing.

1 Introduction

With the advent of the WTO's Doha Development Agenda, as well as the Millennium Development Goals aiming to reduce poverty by 50 percent by the year 2015, poverty impacts of trade reforms have attracted increasing attention. This has been particularly true of agricultural trade reform due to the importance of food in the diets of the poor, relatively higher protection in agriculture, as well as the heavy concentration of global poverty in rural areas where agriculture is the main source of income. Three quarters of the world's poor reside in rural areas (World Bank, 2004), mostly depending for their livelihoods on agriculture. And since changes in primary commodity prices have been identified as one of the important linkages between trade policy and poverty (Winters 2000), current trade policy reform prospects have generated an intense debate about the impacts on poverty. Also it is widely accepted that agricultural commodity prices are inherently volatile due to a combination of inelastic demand and supply, high perishability, high transport costs, and exposure to random climatic shocks. With this background noise in agricultural prices some have rightly argued that the additional price impacts due to trade liberalization might well be undetectable.

In a critique on Cline´s (2004) book on trade policy and poverty, Dani Rodrik made the point that the impact of agricultural domestic support programs in developed economies on world prices are likely to be dwarfed by the inherent volatility of agricultural markets. He based his argument on the comparison of world price outcomes in studies of global trade liberalization with the observed standard deviation of year-to-year price variability in primary commodity markets and concluded that the latter are large, relative to the former. Similar sentiments surfaced frequently from World Bank field staff members in the context of a project on trade and poverty under the Doha Development Agenda (Hertel and Winters, 2006). These verbal remarks stimulated our interest in a more formal empirical analysis of the potential invisibility of poverty impacts of trade policy induced changes.

Literature on poverty impacts of trade reforms in presense of price variability is scarce. The related topics of change in level of food prices on poverty drew attention (Ivanic and Martin 2008) and impacts of trade reforms on income distribution too have been extensively studied (Robbins, 1996; Lunati and O´Connor, 1999). Despite its archetypal framework and therefore limited empirical foundation Bourguignon et al. (2004) developed a framework to assess impact of export price variability on household income volatility. However neither Bourguignon *et al* nor any others have attempted to explore if these trade policy impacts starkly stand out or go unnoticed in the background noise createtd by inherently volatile commodity markets.

The purpose of this study is to test this invisibility hypothesis to see whether trade policy-induced, intended poverty changes are statistically discernable from the random tosses in households' poverty statuses due to agricultural price fluctuations. The focus commodities are staple grains as they represent an important share of the budget for the poorest households. Volatility in staple grains production is modeled by sampling from a distribution of productivity shocks derived from time series analysis of FAO production data. This supply-side volatility is implemented in a Computable General equilibrium (CGE) framework – the agricultural-specific GTAP-AGR model (Keeney and Hertel, 2005). General equilibrium approach permits us to capture the implications of changes in national commodity and factor prices, resulting from alterations in global trade policies as well as uncertainty in world grain yields, while retaining economy-wide consistency. The changed factor and commodity prices impact household income and thereby consumption and utility of the agent. If the agent barely attains or falls short of attaining this pre-shock level of utility with the new post-shock income, they become poor. In the process of generating price volatility, the model also generates the first two moments of distributions for all endogenous variables. We compare the resulting ex ante distribution of poverty headcount, reflecting agricultural prices variability, with ex post distribution of the same when trade reform are implemented in conjunction with price variability. Given that our focus is on staple grains markets, only trade reforms in grains sector are considered. In order to get an adequately broad representation of world's poor, we undertake this analysis for fifteen developing countries in South Asia, Latin America and Sub-Saharan Africa.

The remainder of this study is organized as follows. Methodology used is described in the next section. Section 3 presents the results for the moments of distribution for variables driving poverty headcounts changes before finally evaluating if the poverty headcount distributions across scenarios are statistically different. The caveats, conclusions and policy implications are drawn in the last section.

2 Methodology

2.1 Poverty Headcount Analysis

One of the simplest approaches to poverty headcount analysis is provided by Hertel *et al* 2009. They focus on poverty headcount changes in each household group in the population and provide a first order approximation to such changes in percentage terms, as follows

$$\widehat{H}_{rs} = -\varepsilon_{rs} \cdot \hat{y}^{p}_{rs} = -\varepsilon_{rs} \cdot \sum_j \alpha^{p}_{rsj} \left(\widehat{w}_{rj} - \hat{C}^{p}_{r}\right) \tag{1}$$

The index r denotes region, s the stratum and p signifies that the variable is associated with the poverty level. Any shock to the system alters in all regions, returns to factor j (w_{rj}) and the prices of consumption goods. These two have implications for poverty level of income (y^{p}_{rs}), cost of living for poor (C^{p}_{r}) and therefore strata poverty headcounts (H_{rs}).

Term $\sum_j \alpha^{p}_{rsj} (\widehat{w}_{rj} - \hat{C}^{p}_{r})$ in equation (1) is the percent change in after tax factor income in stratum s of region r, taking into account the cost of living changes for poor in the region. Change in cost of living at the poverty line is the change in household expenditure required to keep utility constant at its poverty level with new prices. It is obtained by solving the household expenditure problem (while also allowing them to change the optimal consumption bundle) for the increase in income required to maintain this level of utility at post-liberalization level of prices.

Apart from the driver variables (factor earnings and cost of living), two more elements play an important role in determining poverty headcount impacts. Coefficient α^{p}_{rsj} is the share of factor earning j in total poverty income and ε_{rs} is income elasticity of poverty in region r stratum s. The higher the income elasticity of poverty greater would the beneficial impact of a given increase in income. Similarly for a given increase in factor earning, the stratum that has 90 percent of its income coming from the concerned factor, would reap greater benefits in terms of poverty headcount reduction, than one with only 10 percent of its income attributable to the factor. Being shares, the summation over factor earnings for any given stratum is one ($\sum_j \alpha^{p}_{rsj} = 1$). In our sample of 15 countries the values for α^{p}_{rsj} range from 0 to 0.99 (Appendix Table A1) while those for ε_{rs} from 0.00 to 8.98 (Appendix Table A2). More details on the elasticities can be found in Hertel *et al* 2009.

Change in total poverty headcount in a region being the sum of strata headcounts, the percentage change in regional headcount can be written as share weighted sum of strata headcounts,

$$\widehat{H}_r = \sum_s \beta_{rs} \cdot \widehat{H}_{rs} \qquad (2)$$

where the shares (β_{rs}) are the share of stratum s in total poverty in the region r. β_{rs} plays an important role in determining how the strata headcount changes get translated into the aggregate regional headcount. For expository purposes if poverty headcount for both Brazil and Uganda fell by 50 percent only for rural diverse stratum ($\widehat{H}_{rs} = 0 \; \forall \; s \neq rural\ diverse$). In this case the regional poverty headcount in Brazil would fall by a mere 1.5 (0.03 x 50) percent while in Uganda by a 37.5 (0.75 x 50) percent. The results are so diverse due to the big difference (0.03 versus 0.75) in the share of poverty population concentrated in the rural diverse stratum in the two countries as can be seen from Appendix Table A2. These shares as well as the elasticities are calculated from the household data for the countries.

Substituting equation (1) in (2) gives the regional headcount in terms of its driving factors

$$\widehat{H}_r = -\sum_s \beta_{rs} \cdot \varepsilon_{rs} \cdot \sum_j \alpha^{p}_{rsj} \left(\widehat{w}_{rj} - \widehat{C}^{p}_{r}\right) \qquad (3)$$

(3) can be further decomposed into changes due to pre-tax factor earnings ($\widehat{w}_{rj}^{m} = \widehat{w}_{rj} - \widehat{T}_r$), tax changes ($\widehat{T}_r$) to ensure revenue neutrality of policy and the cost of living changes due to changed consumption prices.

$$\widehat{H}_r = -\sum_s \beta_{rs} \cdot \varepsilon_{rs} \cdot \sum_j \alpha_{rsj}^{p} \left(\widehat{w}_{rj}^{m} - \hat{y}_r\right) + \varepsilon_r \cdot \widehat{T}_r + \varepsilon_r (\hat{C}_r^{p} - \hat{y}_r) \quad (4)$$

The first term in equation (4) can be called the earnings effect and involves the changes in factor earning of poor relative to national income. The second term is the tax effect and the last term identifies the effect of change in cost of living relative to regional income. The term ε_r is regional poverty elasticity and is defined as poverty share weighted sum of strata poverty elasticities ($\sum_s \beta_{rs} \cdot \varepsilon_{rs}$). As expected and apparent from the equation, an increase in taxes or relative cost of living raises poverty headcount in a region while increased relative factor incomes work towards poverty reduction.

In this framework, the poverty headcount in stratum s of country r falls when real income falls, and the amount by which it falls depends on the density of the population in the neighborhood of the poverty line. Of course, there are many limitations to the use of equation (1). The strata composition here doesn't change. Most importantly, we are only considering changes in poverty headcount. If extremely poor households have very different earnings or spending patterns than those at the poverty line, then it is entirely possible that the poverty headcount might fall relatively little, while the poverty gap fall more significantly or even rise. The virtue of this very simple approach is that it can be readily implemented across a wide range of household strata and countries, thereby permitting us to generalize our findings.

2.2 Global General Equilibrium Model

To calculate the impact of trade policy reforms on poverty headcount as per equation (1), all that is required is to determine the effect of the same on the driving variables, w_{rj} and C_r^p. The inability of Partial Equilibrium type framework to predict the changes in economy wide factor returns, which play a very prominent role in the analysis, leaves us with the option of a General Equilibrium set up to determine the effects of reforms on the drivers of poverty results.

This study employs the GTAP-AGR model of Keeney and Hertel (2005) which is intended to account for specifics of agricultural markets (see Appendix I for details on the model structure and data sources used).

Short-run assumptions on the factor markets are used which mean that land, capital and self-employed labor are immobile. Returns to these factors are combined into sector profits, which correspond to the agricultural and non-agricultural profits reported in the household surveys. Wage and salaried workers are assumed to be mobile within agricultural and non-agricultural sectors, and the region-specific labor supply elasticity of the AGR model determines the limited mobility of labor between agricultural and non-agricultural sectors.[1] In addition, the model is modified to accommodate tax replacement of lost revenue from trade reforms, in the form of a non-distorting uniform *ad valorem* tax on primary factor endowments, making each scenario fiscally neutral.

2.3 Simulations

With so much emphasis on the drivers, the credibility of results hinges very much on whether the model can produce reliable predictions of impacts of trade reforms on the drivers. Inability to separate the effect of reforms on the drivers from that of other factors, leads us to try an alternative approach. We propose to compare how closely the model is able to generate the *historic weather induced volatility* seen in grain prices. This alternative serves as a check on credibility of model results as well as generates volatile grain markets in which visibility of policy impacts is questioned. Therefore simulations here are used for two purposes: to generate the volatility in the model and also for policy experiments. It is implemented by means of stochastic simulations. If the model fails to characterize the price volatility then the results cannot be taken in earnest.

[1] These parameters for developed economies are based on OECD estimates; however, given the lack of information for developing countries, the GTAP-AGR imposes the parameter of Mexico for all other developing regions.

2.3.1 Characterizing Volatility

An approach to modeling uncertainty in world food markets was illustrated by Tyers and Anderson (1992) and Vanzetti (1998), by sampling from a distribution of supply shocks. Hertel, Keeney and Valenzuela (2004) propose the use of region specific time series modeling to remove systematic changes in wheat output, leaving prediction errors that represent yield fluctuations. Following their approach this study employs Autoregressive Moving Average (ARMA) models to characterize systematic changes in staple grains production using their residuals to define the distributions of productivity shocks. We use staple grains production data from the Food and Agriculture Organization for the period 1991 to 2006 (FAOSTAT)[2]. We calculate the shocks for aggregate regions and let the 15 focus countries inherit those of their respective parent region[3].

The model selection is guided by the significance of the AR and MA components, the Akaike Information Criteria (AIC) and autocorrelation in residuals for alternative model specifications. The fourth column in Table 1 describes the model selection for each series. The normalized standard deviation ($\sqrt{V}$) of the residuals from the estimated time series models are shown in the third column of Table 1. These residuals representing variability in production after eliminating the deterministic component show the greatest variation in Former USSR, Sub-Saharan Africa and Eastern Europe. Column second in the table represents the average (mean) production in the region over the entire period in consideration.

Following the approach of Arndt (1996) and Pearson and Arndt (2000), we characterize productivity variation with a symmetric, triangular distribution. The endpoints of the distribution

2 Staple grains mapping from FAO Definition to GTAP Commodities:

GTAP database	FAO Cereals
Wheat	Wheat
Paddy rice	Rice, Paddy
Cereal grains	Barley, Maize, Pop Corn, Rye, Oats, Millet, Sorghum, Buckwheat, Quinoa, Fonio, Triticale, Canary seed, Mixed grain, cereals nes.

3 This assumption considerably restricts the number of stochastic simulations in the model.

are determined by the formula Mean ± $\sqrt{6V}$. These distributions for the aggregate regions serve as the pool from which shocks are drawn randomly for the model simulations.

Formally, if the general equilibrium model is defined in a general form by:

$$G\ (k, e) = 0 \tag{5}$$

where k represents a vector of endogenous variables, and e a vector of exogenous variables. A solution to equation (5) in the form of $k^r(e)$ produces a vector of results of interest $k^r(e) \equiv H(e)$. In our framework, e is the vector of grains productivity shocks which yields distribution of factor and commodity prices (random endogenous variables). The mean and variance for the endogenous variables take the forms:

$$E[H(e)] = \int_{\Omega} H(e) g(e) de \tag{6}$$

$$E\left[(H(e) - E[H(e)])^2\right] = \int_{\Omega} (H(e) - E[H(e)])^2 g(e) de \tag{7}$$

where *g(e)* represents the multivariate density function, and Ω is the region of integration. Arndt(1996) states that treating a general equilibrium simulation as a problem of numerical integration enables us to deal simultaneously with the solution for the general equilibrium and the randomness of exogenous variables. As an alternative to Monte Carlo approaches, we employ the Gaussian Quadrature (GQ) numerical integration technique developed by Stroud (1957) and Haber (1970), and implemented to policy analysis by Devuyst (1993), and DeVuyst and Preckel (1997). They show that an approximating discrete distribution can be obtained based on known lower-order moments of the model parameters. In turn, selectively solving the model based on the moments of this approximate distribution generates results consistent with the Monte Carlo approach, with far fewer simulations required. Implementation of the GQ procedure in the GTAP model is known as Systematic Sensitivity Analysis (SSA) and is documented in Pearson and Arndt (2000). The idea is to solve the same model $2n$ times for different shock values chosen by the GQ; n here is the number of independent shocks in each simulation. With

11 aggregate regions in our model and an independent productivity shock for each region this translates into solving the model 22 times. The results of SSA are then the average of results for all these 22 simulations and the associated standard deviation.

Turning to the results of stochastic simulations; Appendix Table A3 assesses the ability of model to generate the observed variability in prices for the period 1991-2006.

In absence of reforms, we expect the mean of variables to be more or less the same[4] with or without the price variation but for a spread to emerge (which was absent) due to price fluctuations. Table 2 shows the mean and standard deviation of poverty headcounts in presence of weather induced variability in staple grains markets and as can be seen in all the focus countries the means[5] change by less than 1 percent.

2.3.2 Modeling Staples Trade reforms

Table 3 shows the import average applied tariffs in the staples sector for all of the 15 focus countries Mexico has the highest import tariffs for staple grains. The higher the initial tariffs in a country the greater are the expectations from trade liberalization. This study considers a scenario of trade liberalization which involves the complete removal of tariffs and subsidies (exports and production) in all focus, as well as non-focus, countries. To be consistent with the variability being implemented in staple grain production and prices, the attention is paid solely to reforms in staple grains sectors.

Trade reforms are implemented in the stochastic volatility framework to be contrasted with the no reform scenario under the same set up.

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[4] The reason being that nothing in the model has changed and except for that prices are now randomly drawn from a distribution which is symmetric.

[5] Any big numbers in thousands of units can be explained by the presence of a big poverty base (column 5). Note that as the percent change in poverty headcounts now is the average percentage change in the variable across 22 simulations, the decomposition of results though along the lines of deterministic setup is not as straightforward. Most of the analysis in this subsection therefore focuses not on what is driving the means but on a more relevant question that the stochastic framework can answer: *whether the distributions with and without reforms are different.*

3 Results

How the results of a shock are determined, is better understood by explaining the outcomes of a single trade liberalization simulation rather than average results of 22 simulations. This however not being the focus of analysis is the subject of Appendix II.

With the mechanism for one simulation explained systematically (Appendix II), we can resort straight to comparing pre and post reforms distributions of endogenous variables that drive the poverty headcount results. Finally we focus attention on the comparisons of distributions of poverty headcount at the aggregate regional as well as the disaggregate stratum levels.

3.1 Distributions of Driver Variables

The section begins by discussing the mean and standard deviations of driving factors: staple grains consumption prices, cost of living, income and real after tax factor earnings, resulting from stochastic simulations, and compare those to the same when reforms are implemented in a stochastic framework. This would likely give some indication about what to expect in the formal test of significance of differences of means of poverty headcounts. If the moments of distributions for these variables don't much differ across the two scenarios then results for poverty headcounts too would very likely not be distinguishable.

Table 4 presents the results for staple consumption prices, cost of living and income for all 15 countries. The results are reported in difference terms and are to be interpreted as difference in the moment of distribution for a given variable under reform scenario in comparison to base scenario. For example it can be said that post reform consumption price for staple grains in Thailand are about 10.4 percent higher and in Mexico about 11 percent lower than the prices without reforms in the two countries. For Mexico as seen from the deterministic set up policy shocks, most of the change is driven by reduction in prices as a result of removing high tariffs in the country (Table 3). The reforms seem to benefit the countries in Sub-Saharan Africa as from the table one can see that staple prices are from 2 to 7 percent lower and less volatile post reforms. Changes in cost of living and regional income are not so different. Also it is interesting to see that though mean levels (especially for staple grains) show some difference, standard deviations across the scenarios are almost identical except for Sub-Saharan African countries.

Table 5 focuses on a similar comparison of after-tax real factor earnings for the poverty regions. The first panel in the table gives the differences in means while the bottom panel gives the same in standard deviations. A positive number indicates that post liberalization mean or standard deviation for the factor in the country is higher. Thailand, Mexico and Malawi as seen from the table show larger changes for most of their factors. Also along the pattern of results in Table 4 the changes in standard deviations are much less than in means.

The results seem to suggest that Kolmogorov-Smirnov two sample two tail test[6] (henceforth KS test) can be used for a more formal and general test of difference in distributions of consumption prices and factor earnings. The details of this test and the results for staples consumption prices and unskilled wages are provided in Appendix III.

With the mixed results (Table 4 and 5), it is not very clear if the poverty headcount distributions are going to be perceptibly different. Next we test for differences in the distributions of poverty changes under reforms and under inherent price volatility at both country and strata level.

3.2 Distribution of Poverty Headcounts

This section deals with comparing the reform induced poverty impacts against the supply volatility induced effects, to test the hypothesis if both these samples could be statistically emerging from the same population distribution. In absence of information on the population distribution we rely on the non-parametric KS test. Null hypothesis under consideration here is that the distributions pre and post reforms are not statistically different. Table 6 reports the

[6] This test is more suited to cases where there is not much difference in variance (Baumgartner *et al* 1998).

calculated K-S test statistic values and P-values required for rejecting the null hypothesis, for all the focus countries. Figure 1 shows what the results look like visually for two cases – Bangladesh and Mexico – one where they are not perceptible and the other where they are highly perceptible. The figure brings out the point of invisibility hypothesis very clearly, as to how the effects are visibly distinct in one case and while not in the other. A more familiar QQ diagnostic plot is given for all countries in Appendix IV. The closer the scatter points lie to the 45 degree line the more difficult it is to reject the null. Table 7 provides the results of KS test at the strata level to answer the invisibility hypothesis of trade effects. As it shows the answer varies from stratum to stratum within a country.

The broad findings are that short-run poverty changes resulting from liberalizing staples sectors are large enough to be discernable only in Malawi, Mexico and Thailand, of the 15 focus countries in this study. Also even though the results are not perceptible at country level for some cases, a look at a more micro level (stratum) reveals a different result. Similarly for across country comparison while the regional level results for Mexico and Bangladesh look very different; the change in agricultural stratum poverty in both countries is invisible to the same degree (Table 7).

For the regions showing a discernable poverty headcount increase in short and medium term, trade reform may not be the best alternative. In these instances, the policy implication is to allow for longer phases for reform implementation, in combination with specifically targeted support of low-income households. For regions that do see a reduction in poverty headcount in medium to longer term it would be necessary to device a policy to cushion the transition till the long term affects start to materialize and become evident. The results that emerge from stratum level analysis can help target policy intervention (e.g. safety nets).

Though it is not realistic to expect global trade reform negotiations to achieve full liberalization of tariffs and quota imports, and domestic support in agriculture and furthermore of it being restricted only to staple grains, as is the case with the policy experiment here, the experiment is interesting in that it provides and upper limit to impacts that would be seen emerging from the sectors.

Even with this most extreme form of trade liberalization – namely full liberalization – we find that the effects are not statistically visible. So anything short of full liberalization would clearly be less visible and less significant.

4 Conclusions

The results here are sensitive to the level of sector and regional aggregation chosen, in which direction it impacts the results however isn't very clear. Calculations using FAOSTAT data show that measures of observed volatility in output changes considerably depending what aggregation of crops and regions is used, the higher is the aggregation the lower the is the volatility that the model is calibrated to generate. Also as mentioned before the earning specialization of households isn't allowed to change; large shocks may induce a household to switch employment though it is not very likely in the short run. Finally the analysis here concentrates only on population around the dollar per day poverty line and overlooks the details at income levels below it. The results for such population subsections can differ widely.

Despite the shortcoming this study attempts to provide poverty-measures, the potential to account for price fluctuations by proposing the stochastic simulation framework to look at poverty impacts of trade reforms when prices are volatile. We find that the short-run poverty impacts of *full* liberalization of grains' trade are statistically distinguishable from those due to inherent volatility in staple grains markets in only 3 out of the 15 sample countries and of the 3 only Malawi shows an increased poverty headcount mean. So we broadly fail to reject the hypothesis that short run impacts of trade policies are in fact invisible in presence of volatile commodity markets.

In light of the obtained results, international trade and openness are high impact but debatable means of poverty reduction for the lowest income households in countries which do see perceptible results even in short run. For countries experiencing an increase in poverty in the short-run, but expecting a reduction in the medium-term, the policy implication is the necessity to devise some safety net mechanism to help the lowest income households adjust till the longer term gains are realized. For countries showing a discernable increase in poverty in the short-run, and for which there are predictions of increasing poverty in the medium-term, this framework suggests that under the objective of poverty reduction, trade liberalization may not be the best alternative. In these instances, the policy implication is to allow for longer phases for reform implementation, in combination with specifically targeted support of low-income households.

The framework proposed here provides a more general path for future empirical research on trade policy that takes into account price variability in assessing the poverty impacts of trade reform.

References

Arndt, C. 1996. “An Introduction to Systematic Sensitivity Analysis Via Gaussian Quadrature.” GTAP Technical Paper No. 2. Available at: www.gtap.org.

Baumgartner W, P Weiß and H Schindler, 1998. “A Nonparametric Yest for the General Two-Sample Problem”, Biometrics, Vol. 54, No. 3 (Sep., 1998), pp. 1129-1135.

Bourguignon, F., S. Lambert, and A. Suwa-Eisenmann, 2004. “Trade exposure and income volatility in cash-crop exporting developing countries.” European *Review of Agricultural Economics,* Vol 31(3), 369-387.

Cline, W.R., 2004. *Trade Policy and Global Poverty*. Washington, D.C. Institute for International Economics.

Cranfield, J.A.L., P.V. Preckel, J.S. Eales, and T.W. Hertel, 2004. “Simultaneous estimation of an implicit directly additive demand system and the distribution of expenditure — an application of maximum entropy.” *Economic Modelling*, 21(2), 361-385.

DeVuyst, E.A. 1993. “Moment Preserving Approximations of Multivariate Probability Distributions for Decision and Policy Analysis: Theory and Applications.” Ph.D. dissertation, Purdue University.

DeVuyst, E.A., and P.V. Preckel, 1997. “Sensitivity Analysis Revisited: A Quadrature Based Approach.” *Journal of Policy Modeling*. 19(2), 175-85.

Dimaranan, Betina V., Editor (2006). *Global Trade, Assistance, and Production: The GTAP 6 Data Base*, Center for Global Trade Analysis, Purdue University.

FAOSTAT (Food and Agriculture Organization Statistical Database). Internet site: www.fao.org.

Gibonns J D and Chakraborti S, 2003. “Nonparametric Statistical Inference”.

Haber, S. 1970. “Numerical Evaluation of Multiple Integrals.” *SIAM Review* 12:481-525.

Hertel, T.W., R. Keeney, and E. Valenzuela, 2004. “Global Analysis of Agricultural Liberalization: Assessing Model Validity.” Selected paper presented at AAEA Annual Meeting, Denver, Colorado.

Hertel, T.W., and L.A. Winters (eds.), 2006. *Putting Development Back Into the Doha Agenda: Poverty Impacts of a WTO Agreement*. New York: Palgrave Macmillan, co-published with the World Bank.

Hertel, T.W., R. Keeney, M. Ivanic and LA Winters, 2009. "Why Isn't the Doha Development Agenda more Poverty Friendly?" Review of Development Economics, Volume 13(4), p 543-559.

Ivanic, M., 2004. "Reconciliation of the GTAP and household survey data." Technical report, Global Trade Analysis Project.

Ivanic, Maros & Martin, Will, 2008. "Implications of higher global food prices for poverty in low-income countries," Policy Research Working Paper Series 4594, The World Bank.

Keeney, R, and T.W. Hertel, 2005. "*GTAP-AGR: A Framework for Assessing the Implications of Multilateral Changes in Agricultural Policies.*" GTAP Technical Paper Series No.24. Purdue University, West Lafayette, Indiana, U.S.A.

Lunati, M. R., and D. O'Connor, 1999. *Economic opening and the demand for skills in developing countries: a review of theory and evidence*. OCDE/GD(96)182. Paris: OECD.

Pearson, K., and C. Arndt, 2000. *Implementing Systematic Sensitivity Analysis Using GEMPACK*. GTAP Technical Paper No. 3. Internet site: www.gtap.org

Robbins, D. J., 1996. *Evidence on trade and wages in the developing world*. OCDE/GD(96)182. Paris: OECD.

Stroud, A.H. 1957. Remarks on the Disposition of Points in Numerical Integration Formulas, Math. Tables Aids Comput., 11:257-261.

Tyers, R., and K. Anderson, 1992. *Disarray in World Food Markets*. Cambridge: Cambridge University Press.

Vanzetti, D., 1998, *Global Stocks, Price Stability and Food Security*. Report No. 95, Danish Institute for Agricultural and Fisheries Economics, Copenhagen.

Winters, L. Alan. 2000. "Trade and Poverty: Is There a Connection?" in Trade, Income Disparity and Poverty. Ben David, D.; H. Nordstrom and L. A. Winters, eds. Special Study 5, Geneva: WTO.

World Bank. 2004. *Global Economic Prospects 2004 – Realizing the Development Promise of the Doha Agenda*. Washington, D.C.: World Bank.

Table 1: Historical Staple Grains Production and Variability

	Staple Grains		
		Time series modeling	
		Production	
	Average production (Million MT)	Normalized standard regression error [a]	Model ARMA(p,q) [b]
USA – Canada	380.28	4.41	(0,0)
Latin America	109.64	3.73	(0,0)
Western Europe	114.35	3.64	(0,2)
Eastern Europe	188.22	9.70	(0,{2})[c]
Former USSR	70.22	19.20	(0,1)
High Income East Asia	19.98	3.48	(0,0)
South Asia	419.85	1.26	(0,1)
China	419.76	3.41	(1,1)
Middle East North Africa	50.41	5.02	(0,2)
Africa Sub Sahara	16.06	12.77	(1,1)
Oceania	30.67	5.24	(1,1)

Source: Author's calculations based on FAO data, Cereals, 1991-2006.

[a] Endpoints of a symmetric triangular distribution are constructed using these variances of production as: Endpoint = Mean $\pm\sqrt{6}$ standard regression error.

[b] *p* is the number of coefficients for the AR process, *q* is the number of coefficients for the MA process. There are instances where the variation in series is mostly explained by time trend and dummies; and no ARMA terms are found to be significant.

[c] a number in {} brackets indicates that the process only takes that lag, and not the previous one. E.g., the production series in Eastern Europe is fitted with an MA process that takes only lag 2.

Table 2: Ex Ante Mean and Standard Deviation of Poverty Changes Resulting from Grain Prices Fluctuation.

	Distribution of Poverty Headcount Changes		
	Percent change in poverty headcount	in thousands	
	Mean	Mean	Standard deviation
Bangladesh	0.25	112	664
Indonesia	0.07	10	42
Philippines	-0.15	-17	299
Thailand	0.02	0	7
Vietnam	0.18	3	13
Brazil	0.10	22	114
Chile	0.05	0	3
Colombia	0.09	3	18
Mexico	0.13	13	105
Peru	0.10	4	26
Venezuela	0.21	7	32
Malawi	-0.05	-2	6
Mozambique	0.70	43	99
Uganda	-0.67	-116	151
Zambia	0.84	50	132

Source: Authors Calculations using Model Simulation Result

Table 3: Weighted Average Applied Import Tariffs for Staples

Bangladesh	4.65
Indonesia	6.67
Philippines	17.05
Thailand	20.09
Vietnam	3.01
Brazil	0.15
Chile	6.97
Colombia	12.12
Mexico	23.75
Peru	16.73
Venezuela	12.06
Malawi	0.48
Mozambique	3.48
Uganda	5.00
Zambia	3.22

Table 4: Differences in Mean and Standard Deviations Across Scenarios

	Mean			Standard Deviation		
	Staples Consumption Price	Cost of Living	Regional Income	Staples Consumption Price	Cost of Living	Regional Income
Bangladesh	0	0	0	0	0	0
Indonesia	-2	0	0	-1	0	0
Philippines	-2	-1	0	0	0	0
Thailand	10	1	0	1	0	0
Vietnam	-4	-1	0	-2	0	0
Brazil	1	0	0	-1	0	0
Chile	-1	0	0	0	0	0
Colombia	-3	0	0	0	0	0
Mexico	-11	-1	0	-2	0	0
Peru	-4	-1	0	-1	0	0
Venezuela	-3	0	0	-1	0	0
Malawi	-2	-1	-1	-3	-1	-2
Mozambique	-6	-1	-1	-3	-1	-1
Uganda	-7	-2	-2	-10	-2	-3
Zambia	-4	-1	-1	-6	-1	-1

Table 5: Differences in Mean and Standard Deviations of Real After-tax Factor earnings Across Scenarios

	Bangladesh	Indonesia	Philippines	Thailand	Vietnam	Brazil	Chile	Colombia	Mexico	Peru	Venezuela	Malawi	Mozambique	Uganda	Zambia
								Mean							
Land	-1	-1	1	9	1	1	1	0	-7	-2	-1	-2	-2	0	-2
AgUnskl	0	0	0	1	0	0	0	0	0	0	0	-1	0	0	0
AgSkl	0	0	0	1	0	0	0	0	0	0	0	-1	0	-1	0
NagUnskl	0	0	0	-1	0	0	0	0	1	0	0	-1	0	0	0
NagSkl	0	0	0	-1	0	0	0	0	1	0	0	0	0	-1	0
WgUnskl	0	0	0	-1	0	0	0	0	1	0	0	-1	0	0	0
WgSkl	0	0	0	-1	0	0	0	0	1	0	0	0	0	-1	0
AgCap	-1	-1	1	9	1	1	1	0	-4	-2	-1	-2	-2	0	-3
NagCap	0	0	0	-1	0	0	0	0	1	1	0	0	0	-1	0
Transfe	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
								Standard Deviation							
Land	-1	0	0	2	-2	0	0	0	-1	-1	0	0	-2	0	-3
AgUnskl	0	0	0	0	0	0	0	0	0	0	0	2	0	0	1
AgSkl	0	0	0	0	0	0	0	0	0	0	0	2	0	1	1
NagUnskl	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
NagSkl	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
WgUnskl	0	0	0	0	0	0	0	0	0	0	0	2	0	1	0
WgSkl	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
AgCap	-1	0	0	2	-2	0	0	0	0	-1	0	0	-2	0	-3
NagCap	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
Transfe	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 6: K-S Test Statistics, P-Values and Moments of Distributions

	Calculate Test Statistic	Exact P-value	Volatility		Volatility + Staples Trade Liberalization	
			Mean	Standard deviation	Mean	Standard deviation
Bangladesh	0.14	0.87	112	664	85	643
Indonesia	0.14	0.87	10	42	1	35
Philippines	0.27	0.22	-17	299	-186	342
Thailand	0.41	0.05	0	7	-6	8
Vietnam	0.27	0.22	3	13	-3	11
Brazil	0.32	0.22	22	114	40	111
Chile	0.32	0.22	0	3	-1	3
Colombia	0.23	0.39	3	18	-4	18
Mexico	0.59	0.00	13	105	-116	95
Peru	0.27	0.22	4	26	-6	21
Venezuela	0.27	0.22	7	32	1	30
Malawi	0.45	0.02	-2	6	20	35
Mozambique	0.23	0.39	43	99	37	111
Uganda	0.14	0.87	-116	151	-105	133
Zambia	0.14	0.87	50	132	56	149

Table 7: Exact P-Values Required to Reject the Invisibility Hypothesis at Stratum Level Poverty Headcount

	Agric	Non-Agric	RuralLab	UrbanLab	Transf	RuralDiv	Urban Div
Bangladesh	0.39	0.92	0.92	0.92	1	0.92	0.92
Indonesia	0.39	0.63	0.63	0.63	0.63	0.63	0.63
Philippines	0.63	0.63	0.39	0.57	0.63	0.39	0.20
Thailand	0	0.01	0.02	1	0.04	0.01	1
Vietnam	1	0.63	1	1	0.84	0.39	0.39
Brazil	0.57	0.39	0.20	0.20	1	0.84	0.92
Chile	0.57	1	1	1	1	1	1
Colombia	0.20	0.57	0.84	0.84	0.57	0.57	0.84
Mexico	0.39	0	0	0	0.00	0.01	0.01
Peru	0	0.20	0.39	1	0.25	0.39	0.39
Venezuela	1	0.39	0.57	0.57	1	0.92	0.92
Malawi	0.02	0.84	0.57	1	0.06	0.01	0.20
Mozambique	0.20	0.84	0.57	1	0.84	0.57	0.57
Uganda	1	0.84	0.84	0.84	1	0.92	1
Zambia	1	0.92	0.84	0.84	1	0.84	0.84

Figure 1a: Empirical Cumulative Distribution of Poverty Headcount in Mexico

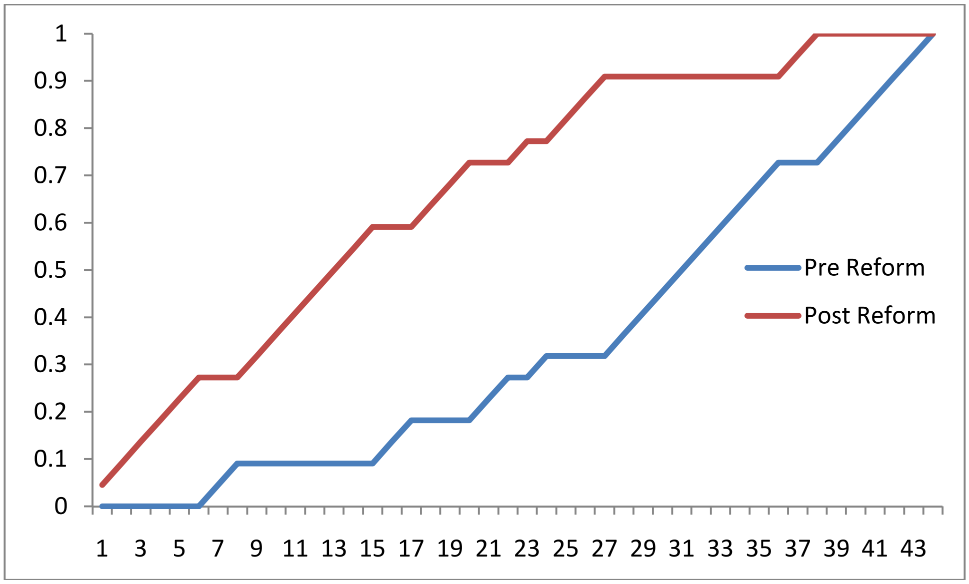
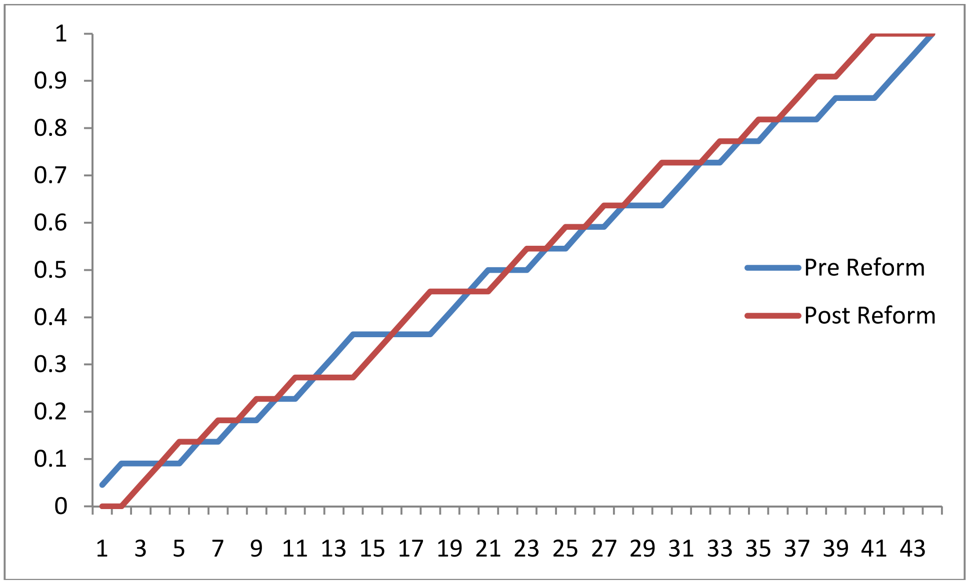


Figure 1b: Empirical Cumulative Distribution of Poverty Headcount in Bangladesh



Source: Model simulation results

APPENDICES
AND
APPENDIX TABLES

Table A1. Earnings Shares (α^{p}_{rsj}) for Strata at $1/day

Country	Land	AgUnskl	AgSkl	AgCap	NagUnskl	NagSkl	NagCap	WgUnskl	WgSkl	Transfe	Total
					AGRICULTURAL						
Bangladesh	0.02	0.94	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Indonesia	0.02	0.95	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Philippines	0.65	0.00	0.00	0.34	0.01	0.00	0.00	0.00	0.00	0.00	1.00
Thailand	0.08	0.80	0.07	0.04	0.00	0.00	0.00	0.00	0.00	0.01	1.00
Vietnam	0.03	0.96	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Brazil	0.02	0.63	0.29	0.07	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Chile	0.23	0.44	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Colombia	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Mexico	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Peru	0.02	0.94	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Venezuela	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Malawi	0.05	0.84	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Mozambique	0.02	0.93	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Uganda	0.29	0.17	0.00	0.52	0.00	0.00	0.00	0.00	0.00	0.03	1.00
Zambia	0.28	0.02	0.00	0.69	0.00	0.00	0.00	0.00	0.00	0.00	1.00
					NON AGRICULTURAL						
Bangladesh	0.00	0.00	0.00	0.00	0.95	0.00	0.04	0.00	0.00	0.00	1.00
Indonesia	0.00	0.00	0.00	0.00	0.94	0.02	0.04	0.00	0.00	0.00	1.00
Philippines	0.00	0.00	0.00	0.00	0.80	0.03	0.16	0.00	0.00	0.00	1.00
Thailand	0.00	0.00	0.00	0.00	0.91	0.06	0.02	0.00	0.00	0.00	1.00
Vietnam	0.00	0.00	0.00	0.00	0.58	0.01	0.40	0.00	0.00	0.01	1.00
Brazil	0.00	0.00	0.00	0.00	0.96	0.04	0.00	0.00	0.00	0.00	1.00
Chile	0.00	0.00	0.00	0.00	0.88	0.09	0.03	0.00	0.00	0.00	1.00
Colombia	0.00	0.00	0.00	0.00	0.97	0.01	0.02	0.00	0.00	0.00	1.00
Mexico	0.00	0.00	0.00	0.00	0.95	0.05	0.00	0.00	0.00	0.00	1.00
Peru	0.00	0.00	0.00	0.00	0.82	0.11	0.07	0.00	0.00	0.01	1.00
Venezuela	0.00	0.00	0.00	0.00	0.98	0.02	0.00	0.00	0.00	0.00	1.00
Malawi	0.00	0.00	0.00	0.00	0.71	0.03	0.26	0.00	0.00	0.00	1.00
Mozambique	0.00	0.00	0.00	0.00	0.62	0.00	0.38	0.00	0.00	0.00	1.00
Uganda	0.00	0.00	0.00	0.00	0.51	0.02	0.46	0.00	0.00	0.00	1.00
Zambia	0.00	0.00	0.00	0.00	0.61	0.01	0.38	0.00	0.00	0.00	1.00

Country	Land	AgUnskl	AgSkl	AgCap	NagUnskl	NagSkl	NagCap	WgUnskl	WgSkl	Transfe	Total
URBAN LABOR											
Bangladesh	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	1.00
Indonesia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.91	0.09	0.00	1.00
Philippines	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.93	0.06	0.00	1.00
Thailand	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.98	0.01	0.00	1.00
Vietnam	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.99	0.00	0.00	1.00
Brazil	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.93	0.07	0.00	1.00
Chile	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.01	0.00	1.00
Colombia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.01	0.00	1.00
Mexico	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.03	0.00	1.00
Peru	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.92	0.07	0.01	1.00
Venezuela	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.97	0.03	0.00	1.00
Malawi	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.83	0.16	0.00	1.00
Mozambique	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00
Uganda	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.32	0.67	0.01	1.00
Zambia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.66	0.34	0.00	1.00
RURAL LABOR											
Bangladesh	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.92	0.07	0.00	1.00
Indonesia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.94	0.06	0.00	1.00
Philippines	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.04	0.00	1.00
Thailand	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.98	0.01	0.01	1.00
Vietnam	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.79	0.18	0.01	1.00
Brazil	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.04	0.00	1.00
Chile	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.98	0.02	0.00	1.00
Colombia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.01	0.00	1.00
Mexico	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00
Peru	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.92	0.07	0.01	1.00
Venezuela	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.04	0.00	1.00
Malawi	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.89	0.10	0.00	1.00
Mozambique	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00
Uganda	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.49	0.00	1.00
Zambia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.79	0.21	0.00	1.00

Country	Land	AgUnskl	AgSkl	AgCap	NagUnskl	NagSkl	NagCap	WgUnskl	WgSkl	Transfe	Total
TRANSFERS											
Bangladesh	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.98	1.00
Indonesia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Philippines	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	1.00
Thailand	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.99	1.00
Vietnam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Brazil	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Chile	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Colombia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Mexico	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Peru	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Venezuela	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Malawi	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Mozambique	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Uganda	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.99	1.00
Zambia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
URBAN DIVERSE											
Bangladesh	0.02	0.20	0.00	0.02	0.19	0.00	0.01	0.43	0.05	0.09	1.00
Indonesia	0.05	0.30	0.00	0.03	0.19	0.01	0.09	0.28	0.00	0.05	1.00
Philippines	0.20	0.00	0.02	0.11	0.15	0.00	0.07	0.33	0.01	0.12	1.00
Thailand	0.02	0.24	0.04	0.01	0.04	0.00	0.01	0.28	0.05	0.30	1.00
Vietnam	0.04	0.43	0.00	0.02	0.11	0.00	0.24	0.02	0.00	0.14	1.00
Brazil	0.00	0.09	0.05	0.02	0.11	0.01	0.00	0.32	0.02	0.38	1.00
Chile	0.07	0.16	0.00	0.10	0.03	0.00	0.00	0.38	0.00	0.26	1.00
Colombia	0.00	0.19	0.00	0.00	0.32	0.00	0.03	0.29	0.00	0.17	1.00
Mexico	0.01	0.11	0.00	0.01	0.08	0.00	0.01	0.48	0.01	0.29	1.00
Peru	0.01	0.23	0.00	0.01	0.28	0.05	0.04	0.20	0.01	0.17	1.00
Venezuela	0.00	0.07	0.00	0.01	0.34	0.01	0.00	0.27	0.02	0.28	1.00
Malawi	0.04	0.28	0.00	0.07	0.04	0.00	0.14	0.19	0.00	0.24	1.00
Mozambique	0.01	0.35	0.00	0.01	0.05	0.00	0.19	0.12	0.00	0.27	1.00
Uganda	0.15	0.13	0.00	0.28	0.06	0.00	0.09	0.14	0.05	0.10	1.00
Zambia	0.01	0.05	0.00	0.03	0.19	0.00	0.15	0.38	0.07	0.10	1.00

Country	Land	AgUnskl	AgSkl	AgCap	NagUnskl	NagSkl	NagCap	WgUnskl	WgSkl	Transfe	Total
RURAL DIVERSE											
Bangladesh	0.01	0.18	0.00	0.01	0.20	0.00	0.03	0.43	0.04	0.10	1.00
Indonesia	0.06	0.32	0.00	0.04	0.20	0.00	0.08	0.26	0.00	0.04	1.00
Philippines	0.22	0.00	0.02	0.12	0.14	0.01	0.08	0.30	0.01	0.11	1.00
Thailand	0.04	0.21	0.03	0.02	0.03	0.01	0.01	0.24	0.07	0.35	1.00
Vietnam	0.01	0.09	0.00	0.00	0.14	0.00	0.55	0.00	0.00	0.21	1.00
Brazil	0.00	0.10	0.04	0.01	0.12	0.00	0.00	0.32	0.01	0.41	1.00
Chile	0.05	0.16	0.00	0.07	0.02	0.00	0.00	0.35	0.00	0.35	1.00
Colombia	0.00	0.22	0.00	0.00	0.30	0.00	0.02	0.22	0.02	0.21	1.00
Mexico	0.01	0.14	0.00	0.01	0.06	0.00	0.01	0.48	0.00	0.30	1.00
Peru	0.02	0.20	0.00	0.03	0.30	0.07	0.11	0.12	0.00	0.14	1.00
Venezuela	0.00	0.09	0.00	0.00	0.32	0.01	0.00	0.28	0.04	0.25	1.00
Malawi	0.03	0.38	0.00	0.06	0.07	0.00	0.11	0.08	0.00	0.27	1.00
Mozambique	0.01	0.43	0.00	0.02	0.07	0.00	0.20	0.07	0.00	0.20	1.00
Uganda	0.14	0.15	0.00	0.26	0.06	0.00	0.14	0.08	0.06	0.10	1.00
Zambia	0.01	0.03	0.00	0.03	0.20	0.00	0.13	0.43	0.04	0.12	1.00

Source: Reviewer’s Appendix Part II.2, Hertel et al 2009.

Table A2: Income Elasticity of Poverty Headcount and Stratum Shares in Regional Poverty Headcount (at $1/day)

	Strata							
Country	Agric.	Non-Agric.	Urban Labor	Rural Labor	Transfer	Urban Diverse	Rural Diverse	Total
				Income Elasticity of Poverty Headcount				
Bangladesh	1.64	2.02	1.58	0.63	0.56	1.74	1.09	1.24
Indonesia	2.35	2.14	2.38	2.89	1.17	2.58	2.87	2.47
Philippines	2.25	1.96	2.98	2.44	1.69	2.42	1.98	2.15
Thailand	2.30	2.42	2.98	2.45	2.78	2.42	2.59	2.57
Vietnam	0.48	1.12	2.81	8.98	0.84	0.86	1.01	0.98
Brazil	0.75	1.28	1.94	2.19	0.34	3.63	2.69	1.35
Chile	1.90	2.24	2.06	1.55	2.45	2.29	2.60	2.18
Colombia	0.79	0.60	1.73	1.72	0.93	1.14	1.00	0.82
Mexico	1.73	1.90	3.33	2.08	2.28	1.63	1.80	2.02
Peru	1.50	1.32	2.37	1.73	0.44	1.09	1.05	1.07
Venezuela	0.69	1.16	2.57	2.17	0.01	1.72	1.53	1.20
Malawi	0.49	0.30	2.26	1.97	0.43	1.04	0.76	0.58
Mozambique	0.28	0.94	0.97	0.76	0.48	1.58	0.99	0.64
Uganda	0.28	0.40	1.71	0.34	0.01	0.36	0.21	0.24
Zambia	0.00	0.64	2.28	0.91	0.45	1.29	0.37	0.61
				Stratum Share in Poverty Population				
Bangladesh	0.15	0.13	0.04	0.22	0.03	0.07	0.37	1.00
Indonesia	0.42	0.12	0.02	0.07	0.04	0.06	0.28	1.00
Philippines	0.12	0.06	0.03	0.05	0.03	0.23	0.49	1.00
Thailand	0.06	0.02	0.00	0.06	0.11	0.07	0.68	1.00
Vietnam	0.04	0.11	0.00	0.00	0.05	0.10	0.70	1.00
Brazil	0.14	0.09	0.24	0.15	0.32	0.04	0.03	1.00
Chile	0.26	0.01	0.09	0.09	0.28	0.15	0.12	1.00
Colombia	0.28	0.43	0.03	0.04	0.12	0.05	0.04	1.00
Mexico	0.05	0.06	0.05	0.12	0.28	0.14	0.29	1.00
Peru	0.07	0.35	0.01	0.02	0.22	0.11	0.23	1.00
Venezuela	0.08	0.24	0.17	0.10	0.28	0.08	0.05	1.00
Malawi	0.54	0.11	0.00	0.03	0.07	0.01	0.25	1.00
Mozambiqe	0.41	0.13	0.01	0.05	0.14	0.06	0.19	1.00
Uganda	0.10	0.04	0.00	0.03	0.02	0.07	0.75	1.00
Zambia	0.34	0.23	0.10	0.07	0.07	0.09	0.11	1.00

Source: Hertel et al 2009

Table A3: Comparing Model Generated with Historic Price Volatility

	Historic Range	Model Results
Bangladesh	5-12	14
Indonesia	9-19*	11
Philippines	10-13*	14
Thailand	11-14	7
Vietnam	-	-
Brazil	11-20	12
Chile	7-21	11
Colombia	4-10	15
Mexico	7-9	9
Peru	6-15	16
Venezuela	6-11	23
Malawi	21-30	59
Mozambique	16-20	64
Uganda	-	-
Zambia	-	-

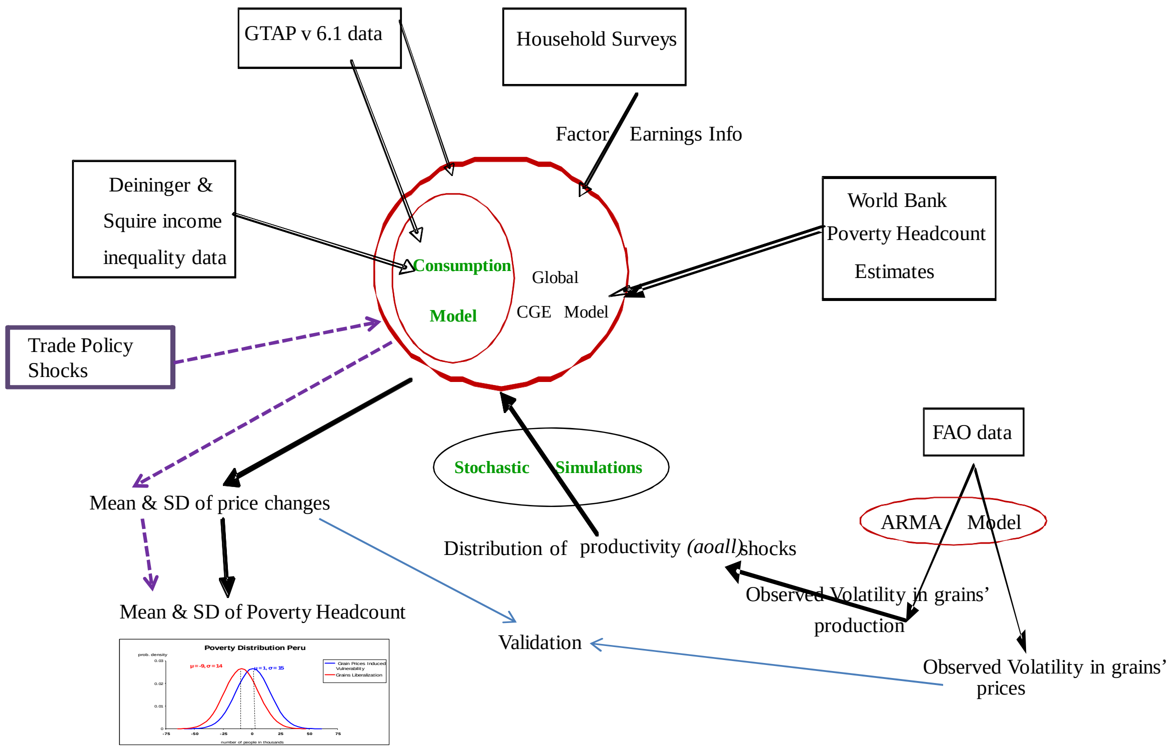
Source: FAO PriceStat Data 1991-2006, and Model Simulation results

* FAO data on Wheat is not available for Indonesia and Philippines; so the range reflects the price volatility of rice and coarse grains only

- Data on none of the crops is available for Vietnam, Uganda and Zambia.

APPENDIX I
Model Structure and Data Sources

Modeling structure and data used in this study is outlined in figure below.



The model uses factor earnings information from household surveys (processed and reconciled with the GTAP data by Ivanic 2004) and World Bank's country poverty headcount estimates along with the GTAP database version 6.1 (Dimaranan 2006) as inputs into the CGE framework. The parameters of consumption demand equations (An Implicit Direct Additive Demand System; Cranfield 2004) are estimated using Deininger and Squire Income distribution data (1996) and GTAP version 6.1. Unlike some earlier studies we model the poverty consumption response to shocks within the CGE framework. This integration of the two, operating in a single framework, ensures consistency of results. Equations determining poverty headcount changes too operate within the CGE model.

Uncertainty in grain supplies is implemented in the model through a series of stochastic productivity shocks, inferred from FAO production data using Autoregressive Moving Average models. These simulations also yield distributions of consumer and factor price changes. The ability of model to reproduce the historic volatility in prices is assessed, which we call the validation exercise. Essentially we compare the price volatility that the model generates in the attempt to replicate production volatility. Again use has been made of FAO price data for the years 1991-2005.

Trade policy reforms in grains, modeled in combination with the same stochastic productivity shocks produce a second set of distributions of consumer and factor price changes and thereby distributions of consumption, utility and poverty headcount. The assessment of the significance of difference of the two sets of distributions of poverty headcount is based on a non-parametric test. If the critical value exceeds the absolute test statistic value we fail to reject the null hypothesis that there is no significant statistical difference in of two distributions and therefore conclude that impacts of reforms are not statistically significantly perceptible.

The level of aggregation in the model is defined at 34 regions and 23 sectors. Sector aggregation is provided in Table A4. Regional aggregation describes major trading blocs, and singles out 15 developing countries for which detailed household survey information is available (Table A5). Table A6 lists the 15 focus countries and their economic indicators.

Table A4: Sector Aggregation

No.	GTAP Commodity	TRAD comm	AIDADS comm
1	Paddy rice	Rice	grain
2	Wheat	Wheat	grain
3	Cereal grains nec	Crsgrns	grain
4	Vegetables, fruit, nuts	OthCrps	fruits
5	Oil seeds	Oilseeds	grain

6	Sugar cane, sugar beet	Sugar	sugar
7	Plant-based fibers	Cotton	mfg
8	Crops nec	OthCrps	fruits
9	Cattle,sheep,goats,horses	Cattle	meat
10	Animal products nec	NRumin	meat
11	Raw milk	Milk	dairy
12	Wool, silk-worm cocoons	TextAppl	mfg
13	Forestry	Res	mfg
14	Fishing	Fish	meat
15	Coal	Utility	svcs
16	Oil	Res	mfg
17	Gas	Utility	svcs
18	Minerals nec	HvyMnfcs	mfg
19	Meat: cattle,sheep,goats,horse	PrBeef	meat
20	Meat products nec	PrNRumn	meat
21	Vegetable oils and fats	PrOilsd	oil
22	Dairy products	PrDairy	dairy
23	Processed rice	PrRice	grain
24	Sugar	PrSugar	sugar
25	Food products nec	OthFdBev	othrproc
26	Beverages and tobacco products	OthFdBev	othrproc
27	Textiles	TextAppl	mfg
28	Wearing apparel	TextAppl	mfg
29	Leather products	TextAppl	mfg
30	Wood products	HvyMnfcs	mfg
31	Paper products, publishing	HvyMnfcs	mfg
32	Petroleum, coal products	Res	mfg
33	Chemical,rubber,plastic prods	HvyMnfcs	mfg
34	Mineral products nec	HvyMnfcs	mfg
35	Ferrous metals	HvyMnfcs	mfg
36	Metals nec	HvyMnfcs	mfg
37	Metal products	HvyMnfcs	mfg
38	Motor vehicles and parts	HvyMnfcs	mfg
39	Transport equipment nec	Srvcs	svcs
40	Electronic equipment	HvyMnfcs	mfg
41	Machinery and equipment nec	HvyMnfcs	mfg
42	Manufactures nec	HvyMnfcs	mfg
43	Electricity	Utility	svcs

44	Gas manufacture, distribution	Utility	svcs
45	Water	Utility	svcs
46	Construction	Srvcs	svcs
47	Trade	Srvcs	svcs
48	Transport nec	Srvcs	svcs
49	Sea transport	Srvcs	svcs
50	Air transport	Srvcs	svcs
51	Communication	Srvcs	svcs
52	Financial services nec	Srvcs	svcs
53	Insurance	Srvcs	svcs
54	Business services nec	Srvcs	svcs
55	Recreation and other services	Srvcs	svcs
56	PubAdmin/Defence/Health/Educat	Srvcs	svcs
57	Dwellings	Srvcs	svcs

Table A5. Regional Aggregation

Regions	Original 92 GTAP regions
Oceania	Australia; New Zealand, Rest of Oceania
High Income East Asia	Singapore; Japan; Korea; Taiwan.
China	China.
South Asia	Bangladesh; Indonesia; India; Pakistan; Philippines; Thailand; Vietnam; Rest of South East Asia; Rest of South Asia
USA Canada	Canada; United States.
Latin America	Brazil; Chile; Colombia; Mexico; Peru; Venezuela; Rest of South America; Rest of Central America and Caribbean.
Eastern Europe	Austria; Belgium; Denmark; Finland; France; Germany; United Kingdom; Greece; Ireland; Italy; Luxembourg; Netherlands; Portugal; Spain; Sweden.
Western Europe	Switzerland; Rest of EFTA; Albania; Bulgaria; Croatia; Cyprus; Czech Republic; Hungary; Malta; Poland; Romania; Slovakia; Slovenia; Estonia; Latvia; Lithuania; Turkey.
Former Soviet Union	Russian Federation; Rest of Former Soviet Union.
Middle East North Africa	Rest of Middle East; Morocco; Tunisia; Rest of North Africa.
Sub Saharan Africa	Mozambique; Malawi; Tanzania; Uganda; South Africa; Zimbabwe; Rest of Sub-Saharan Africa.

<u>Regions/countries for which there is available household survey data to conduct poverty analysis</u>

Asia	Bangladesh, Indonesia, Philippines, Thailand, Vietnam
Latin America	Brazil, Chile, Colombia, Mexico, Peru, Venezuela
Sub-Saharan Africa	Malawi, Mozambique, Uganda, Zambia

Table A6: Economic Indicators. Focus Regions of Poverty Analysis

	Population (in million) 2001	Poverty Population (in million)	GDP per capita PPP (current $) 2001	Agriculture value added as a % of GDP 2001	Survey year
Bangladesh	140.9	44.84	1,613	24.1	1996
Indonesia	214.3	15.12	3,020	17.0	1993
Philippines	77.1	11.38	3,919	14.9	1999
Thailand	61.6	1.2	6,452	9.1	1996
Vietnam	79.2	1.53	2,103	23.2	1998
Brazil	174.0	23.01	7,571	6.1	1998
Chile	15.4	0.29	9,354	8.8	1998
Colombia	42.8	4.01	6,050	14.0	1998
Mexico	100.5	9.45	8,738	4.2	2000
Peru	26.0	4.4	4,699	8.5	1999
Venezuela	24.6	3.26	5,763	5.0	1998
Malawi	11.6	4.24	582	36.2	1998
Mozambique	18.2	6.13	*1,050	26.7	2003
Uganda	24.2	17.25	1,291	36.6	1999
Zambia	10.6	6.02	790	22.1	1998

*in 2002. Sources: FAO, World Bank: World Development Indicators, countries' surveys.

APPENDIX II
Results of Trade Reforms in Deterministic Framework

With slight modifications, equation (4) can be rewritten in terms of change in poverty headcount in thousands of units rather than percent changes:

$$\Delta H_r = (H_r/100)\{-\sum_s \beta_{rs} \cdot \varepsilon_{rs} \cdot \sum_j \alpha_{rsj}^{p} \left(\widehat{w}_{rj}^{m} - \hat{y}_r\right) + \varepsilon_r \cdot \widehat{T}_r + \varepsilon_r(\hat{C}_r^{p} - \hat{y}_r)\}$$

where $\widehat{H}_r = (\Delta H_r/H_r)100$. The term $(H_r/100)$ emphasizes the importance of the initial poverty headcount in the country, which along with the poverty elasticities are applied to the percentage changes in endogenous variables. For any given level of elasticity and changes in factor earnings, taxes and cost of living, the higher the poverty base the higher would be the magnitude of headcount changes.

Tables A7 and A8 show the effect of staples trade liberalization on each of the three components alluded to in equation (4) and the decomposition of changes in poverty headcount. Looking at the results, we do not expect to get the clear sign consistency of results that Hertel *et al* 2009 find in their study which employs the same deterministic framework. We instead get a mixed set here, however our results are not strictly comparable to theirs; the reason being twofold. Unlike them our focus on volatility restricts the reforms to staple grains, while they undertake the liberalization for all of agriculture. Also we consider the effects of liberalization by all the regions together. The effects of poor and non-poor country reforms in isolation (focused in Hertel et al 2009) work in the opposite directions. Effect of OECD country reforms works towards increasing the world prices and therefore benefitting the factors employed in agriculture in the poor countries but at the same time increased consumption prices work towards increasing the cost of living in the poor countries. On the other hand a reduction in import tariffs in poor countries reduces the cost of living but also the import tariff revenue. The results in the Tables A7 and A8 depend on which effects dominate.

The last two columns in the Table A7 give the change in power of tax and the change in relative cost of living. A negative tax number is to be interpreted as an increase in taxes and vice-versa; accordingly one observes a reduction in poverty headcount (Table A8 column 3) associated with positive changes in power of tax.

Relative cost of living and poverty headcount attributable to it falls for all but Thailand, Brazil and Malawi; this can be traced to increased consumption prices for staple grains in Thailand (10.4 percent) and Brazil (1.8 percent) while for Malawi though the staple consumption prices fall the greater proportionate fall in income (-0.4 percent) that drives the result (Table A9). The increase in staples price in Thailand are driven solely due increased price of rice (20 percent) owing to increase in rice export demand. For Brazil the increased consumption prices reflect the increased exports demand for rice and coarse-grains.

In terms of factor earnings, the non-agricultural and economy wide wages (both skilled and unskilled) rise in all countries except Thailand and Brazil, therefore raising expectations that the non-agriculture and urban strata (which derive a greater proportion of their incomes from the factors mentioned) would show a reduction in poverty headcounts. Table A10 provides for all strata region pairs, the results equivalent to Table A8; and as expected the row titled earnings for strata non-agriculture and urban labor does indeed show a reduction in poverty headcount across all countries but the two aforementioned. In terms of numbers at the country level (Table A8) the biggest reduction of 212000 due to factor earning effects is seen in Philippines while the biggest unfavorable outcome is observed for Indonesia with poverty headcount increasing by 61000. Table A7 supports and explains these results. Note that all factor earnings in Philippines witness an increase. In case of Indonesia returns to agricultural factors fall; this combined with the fact that 70 percent (Table A2) of population in the country is concentrated in agriculture, explains why earnings' contribution to poverty headcount is big and positive. Another small result that stands out here is that the magnitude of change in factor earnings is always much larger for land

and agricultural capital, it is so because these two factors are fixed and cannot move across alternative uses.

It is important to note that the poverty headcount results at both regional and strata level, depend not only on how big are factor earning changes but also the poverty elasticities and the share of strata in total regional poverty. Table A2 in appendix provides these numbers. This can explain for example why in Bangladesh despite a modest increase in non-agricultural earnings and wages in comparison to some other countries, the non-agriculture and rural labor strata witness higher poverty reduction. As can be seen from the Table A2 that the country’s poverty elasticity of non-agricultural (2.02) and poverty share of rural diverse labor (37 percent) are quite high.

Table A7: Affect of Staples Trade Reforms on Drivers of Regional Poverty Headcount

Country	Land	AgUnskl	AgSkl	AgCap	NagUnskl	NagSkl	NagCap	WgUnskl	WgSkl	Transfe	Tax	Cost of Living
Bangladesh	-0.38	0.01	0.01	-0.38	0.06	0.06	0.07	0.06	0.06	0	-0.02	-0.02
Indonesia	-1.13	-0.28	-0.18	-1.13	0.13	0.18	0.17	0.04	0.18	0	-0.04	-0.22
Philippines	1.77	0.58	0.47	1.77	0.39	0.32	0.41	0.47	0.32	0	-0.48	-0.30
Thailand	9.45	1.77	1.51	9.44	-0.51	-0.45	-0.61	-0.12	-0.45	0	-0.12	0.47
Vietnam	2.77	0.56	0.52	2.76	0.20	0.21	0.20	0.25	0.21	0	-0.34	-0.33
Brazil	1.49	-0.05	-0.04	1.49	-0.07	-0.05	-0.09	-0.07	-0.05	0	0.00	0.04
Chile	0.58	0.09	0.08	0.58	0.09	0.08	0.09	0.09	0.08	0	-0.09	-0.06
Colombia	-0.67	0.00	0.00	-0.67	0.12	0.10	0.16	0.11	0.10	0	-0.07	-0.23
Mexico	-7.76	-0.66	-0.60	-4.59	0.08	0.09	0.13	0.01	0.08	0	0.09	-0.70
Peru	-2.29	-0.20	-0.15	-2.31	0.18	0.16	0.37	0.10	0.16	0	-0.13	-0.26
Venezuela	-0.97	-0.04	-0.04	-0.97	0.08	0.07	0.08	0.06	0.07	0	-0.03	-0.11
Malawi	-1.09	0.13	0.16	-1.08	0.20	0.20	0.20	0.17	0.20	0	0.05	0.21
Mozambique	-1.47	-0.03	0.03	-1.47	0.15	0.16	0.17	0.10	0.16	0	0.00	-0.27
Uganda	-0.50	0.02	0.12	-0.50	0.14	0.16	0.15	0.06	0.16	0	0.00	-0.03
Zambia	-0.32	0.00	0.02	-0.35	0.08	0.09	0.10	0.06	0.09	0	-0.04	-0.06

Table A8: Decomposition of Change in Regional Poverty Headcount ('000)

	Earnings	Tax	COL	Total
Bangladesh	-19	8	-11	-22
Indonesia	61	14	-83	-9
Philippines	-212	105	-72	-179
Thailand	-24	2	15	-7
Vietnam	-4	4	-5	-5
Brazil	13	-1	14	25
Chile	-1	0	0	-1
Colombia	-2	2	-8	-8
Mexico	18	-10	-135	-127
Peru	-2	5	-12	-9
Venezuela	-2	1	-4	-5
Malawi	0	-1	5	4
Mozambique	-1	0	-11	-12
Uganda	6	0	-1	5
Zambia	-2	2	-2	-3

Table A9: Affect of Staples Trade Reforms on Staple Consumption Prices and Cost of Living (percent change)

	Staple Price	Relative Cost of Living	Cost of Living	Regional Income
Bangladesh	0.1	-0.02	-0.04	-0.02
Indonesia	-1.8	-0.22	-0.37	-0.15
Philippines	-1.4	-0.30	-0.70	-0.41
Thailand	10.4	0.48	0.91	0.43
Vietnam	-1.9	-0.33	-0.59	-0.27
Brazil	1.8	0.04	0.14	0.10
Chile	-0.7	-0.06	-0.20	-0.14
Colombia	-2.9	-0.23	-0.35	-0.12
Mexico	-11.1	-0.70	-0.76	-0.06
Peru	-4.3	-0.26	-0.53	-0.27
Venezuela	-2.5	-0.11	-0.13	-0.02
Malawi	0.0	0.21	-0.19	-0.40
Mozambique	-3.5	-0.27	-0.38	-0.11
Uganda	-0.2	-0.03	-0.29	-0.26
Zambia	0.2	-0.05	-0.10	-0.05

Table A10: Decomposition of Strata Poverty Headcount by Earnings, COL and Tax contributions

	Bangladesh	Indonesia	Philippines	Thailand	Vietnam	Brazil	Chile	Colombia	Mexico	Peru	Venezuela	Malawi	Mozambique	Uganda	Zambia
Agric															
Earnings	1	47	-51	-5	0	-2	-1	0	6	1	0	1	1	2	0
Tax	2	6	14	0	0	0	0	1	-1	1	0	-1	0	0	0
COL	-2	-33	-9	1	0	1	0	-2	-6	-1	0	2	-2	0	0
Total	1	20	-46	-4	0	-1	0	-1	-1	1	0	3	-1	2	0
Non-Agric															
Earnings	-7	-5	-5	0	0	2	0	-1	-1	-4	-1	0	-1	0	-1
Tax	2	2	6	0	1	0	0	1	-1	3	0	0	0	0	0
COL	-2	-9	-4	0	-1	1	0	-2	-8	-5	-1	0	-2	0	0
Total	-8	-12	-3	1	0	3	0	-3	-10	-7	-1	0	-3	0	-1
Urban Lab															
Earnings	-1	0	-4	0	0	7	0	0	0	0	-1	0	0	0	-1
Tax	0	0	4	0	0	-1	0	0	-1	0	0	0	0	0	1
COL	-1	-1	-3	0	0	5	0	-1	-11	0	-2	0	0	0	-1
Total	-2	-1	-3	0	0	11	0	-1	-13	0	-2	0	0	0	-1
Rural Lab															
Earnings	-3	-1	-6	0	0	5	0	0	0	0	0	0	0	0	0
Tax	1	1	7	0	0	0	0	0	-2	0	0	0	0	0	0
COL	-1	-7	-4	1	0	3	0	-1	-17	0	-1	1	-1	0	0
Total	-4	-7	-4	1	0	8	0	-1	-19	0	-1	0	-1	0	0
Transf															
Earnings	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Tax	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
COL	0	-2	-2	2	0	1	0	-1	-42	-1	0	0	-1	0	0
Total	0	-2	-2	2	0	1	0	-1	-42	-1	0	0	-1	0	0
Urban Div															
Earnings	-2	3	-52	-1	-1	0	0	0	4	0	0	0	0	1	0
Tax	1	1	27	0	0	0	0	0	-1	1	0	0	0	0	0
COL	-1	-5	-19	1	0	2	0	-1	-15	-1	0	0	-2	0	0
Total	-2	-2	-43	0	-1	2	0	-1	-13	-1	-1	0	-2	1	0
Rural Div															
Earnings	-7	18	-93	-19	-2	0	0	0	9	1	0	0	0	4	0
Tax	2	4	47	2	3	0	0	0	-3	1	0	0	0	0	0
COL	-4	-27	-33	10	-4	1	0	0	-35	-3	0	2	-3	-1	0
Total	-8	-5	-79	-7	-3	1	0	0	-29	-1	0	1	-3	3	0

APPENDIX III
The Kolmogorov-Smirnov Test and Results for Staple Prices

We use this test to check if the distributions of staple prices for each country in our sample can statistically be originating from the same underlying distribution. Note that though the extreme values for productivity shocks are calculated under the assumption of a symmetric triangular distribution it does not imply that the shocks yield the same distribution or distribution shape for the endogenous variables that it generates as solutions. It is the absence of information about distribution of the endogenous variables that makes us rely on non-parametric test.

The KS test used here is the general two sample non-parametric test which tests the null hypothesis that the two samples are drawn from the same distribution (irrespective of what exactly that distribution might be). The basic idea behind the test is to compare the cumulative distribution functions of the two samples and evaluate how close together the two lie.

Briefly let there be two variables p and t with samples $P_1 \ldots\ldots\ldots P_m$ and $T_1 \ldots\ldots\ldots T_n$, of size m and n. Let their CDFs be denoted $F_m(p)$ and $F_n(t)$. The null hypothesis is testing against a general alternative where

$H_0: F_m(p) = F_n(t) \qquad and \qquad H_A: F_m(p) \neq F_n(t)$

In absence of knowledge about the true distribution we use an empirical (sample counterpart) distribution functions $S_m(p)$ and $S_n(t)$ shown to be a consistent point estimators of the respective true CDFs.

The test statistic $D_{m,n} = max|S_m(p) - S_n(t)|$, if greater than critical value c_α, we can reject the null at α level of significance; else we fail to reject that the two distributions are statistically different. More details on the test can be found in Gibonns and Chakraborti 2003.

To empirically implement this test, we gather the solution for staples prices from each of the 22 simulations and have two such samples of 22 observations each (m = n = 22) corresponding to pre and post trade reform. The corresponding hypotheses stated in economic terms are –

$H_0: Impacts\ of\ Trade\ Policy\ Are\ Satistically\ Invisible$

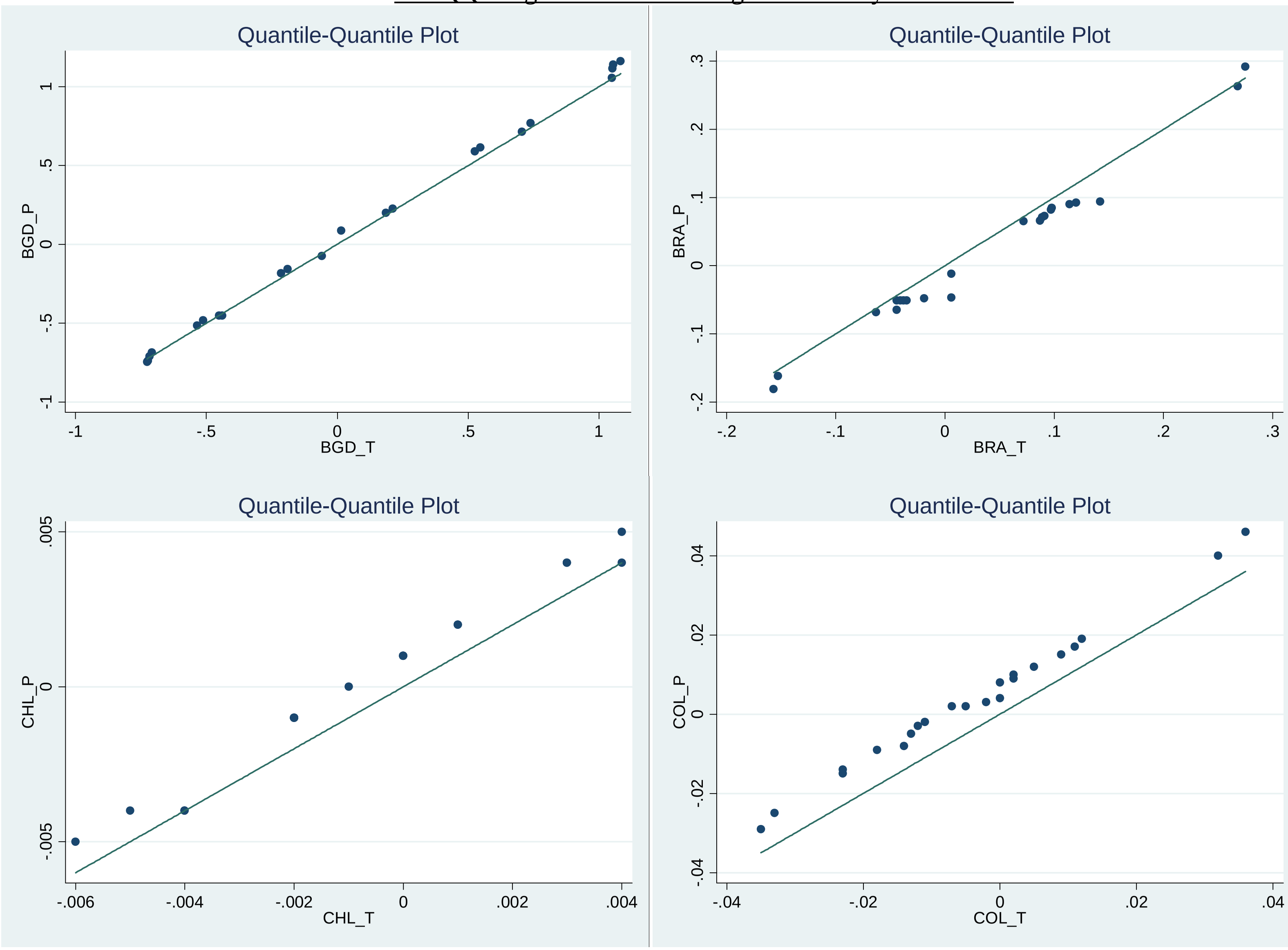
$H_A: Impacts\ of\ Trade\ Policy\ Are\ Statistically\ Visibly\ Different$

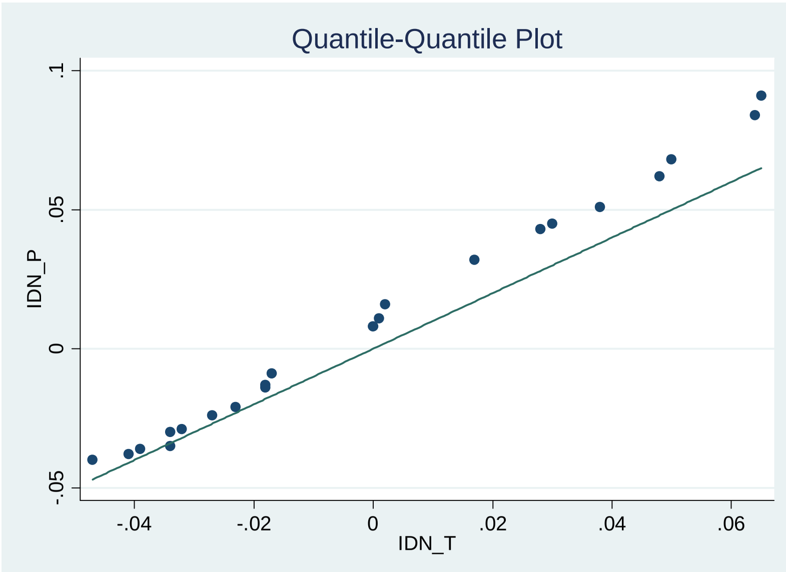
Table A11: KS P-Values For Rejecting the Null (No Difference in Drivers' Distributions Across Scenarios)

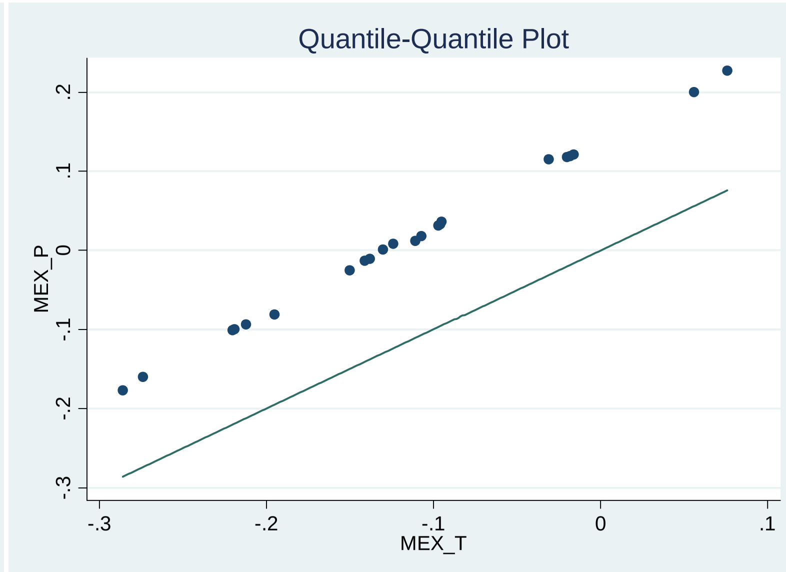
	Staples Price	Unskilled Wages*
Bangladesh	1	0.92
Indonesia	0.84	0.63
Philippines	0.84	0.39
Thailand	0	0.001
Vietnam	0.20	0.39
Brazil	0.39	0.20
Chile	0.63	0.92
Colombia	0.20	0.57
Mexico	0.001	0
Peru	0.02	0.39
Venezuela	0.57	0.39
Malawi	1	0.39
Mozambique	0.84	0.57
Uganda	0.92	0.92
Zambia	0.92	0.57

*Unskilled Wages are the most important factor earnings with four of the seven strata deriving a significant portion of total income from unskilled wages (Table A1).

APPENDIX IV
The QQ Diagnostic Plots for Regional Poverty Headcounts




Quantile-Quantile Plot
IDN_P
-.05
0
.05
.1
-.04
-.02
0
.02
.04
.06
IDN_T


Quantile-Quantile Plot
MEX_P
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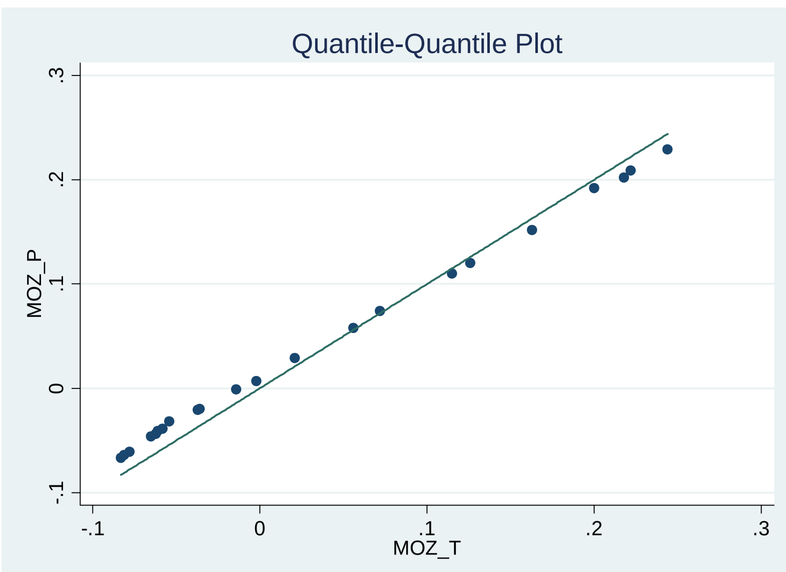
-.2
-.1
0
.1
.2
-.3
-.2
-.1
0
.1
MEX_T


Quantile-Quantile Plot
MOZ_P
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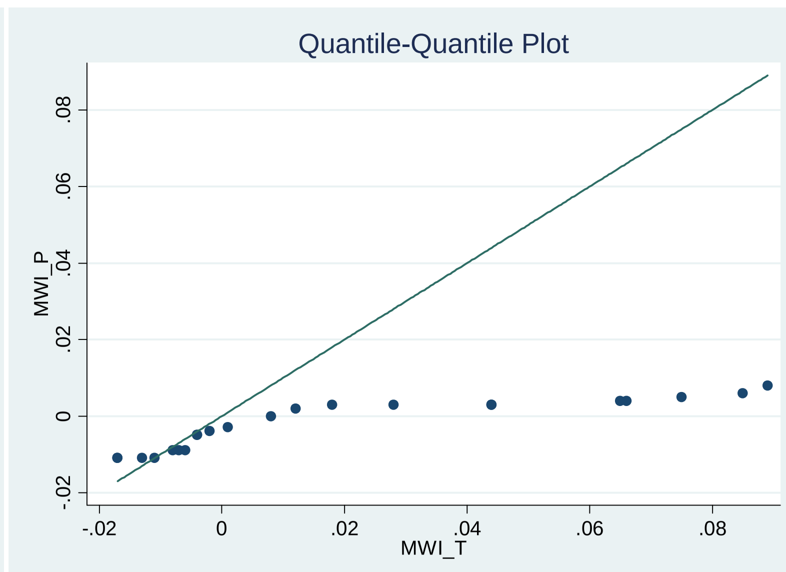
0
.1
.2
.3
-.1
0
.1
.2
.3
MOZ_T


Quantile-Quantile Plot
MWI_P
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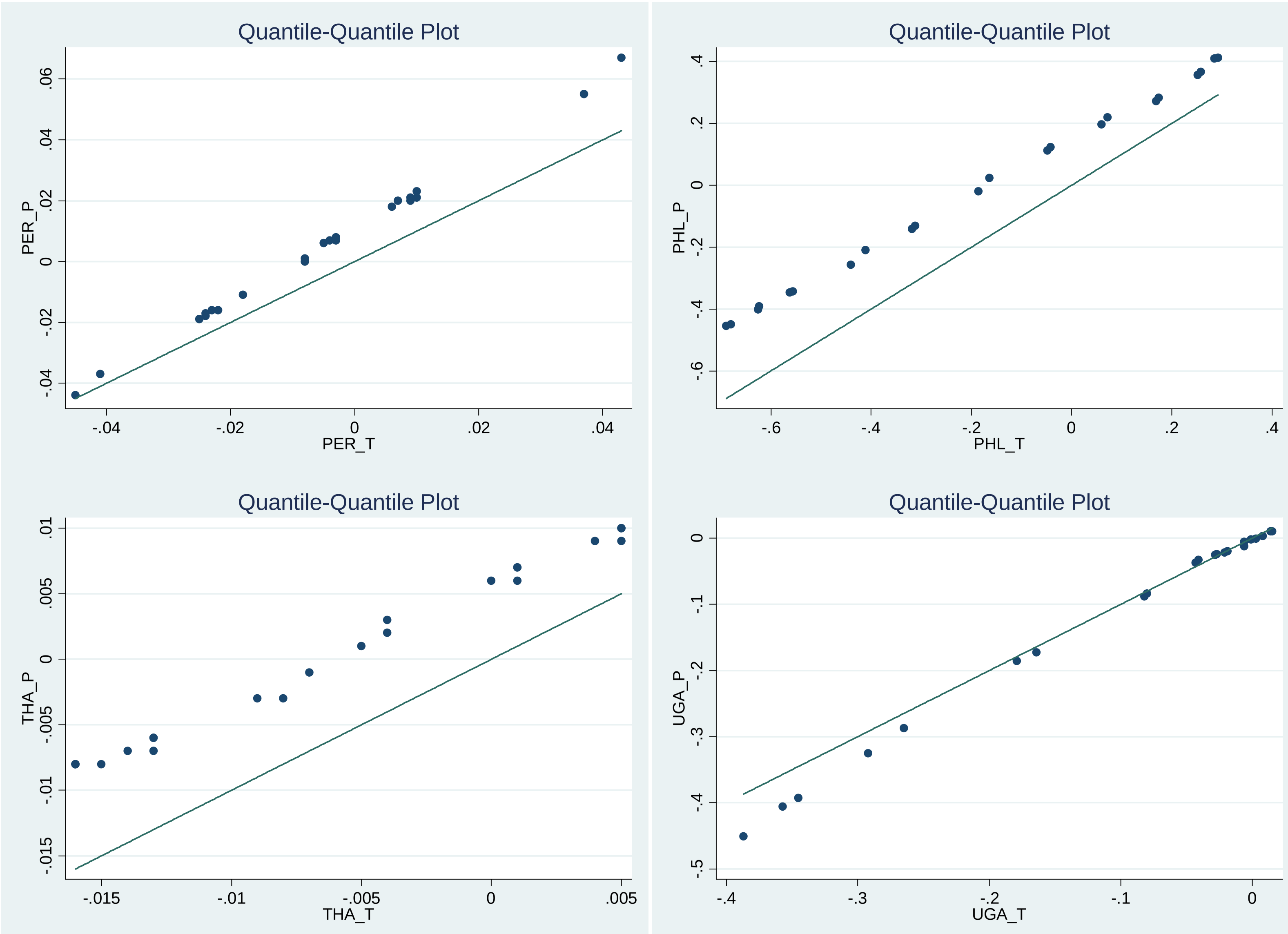
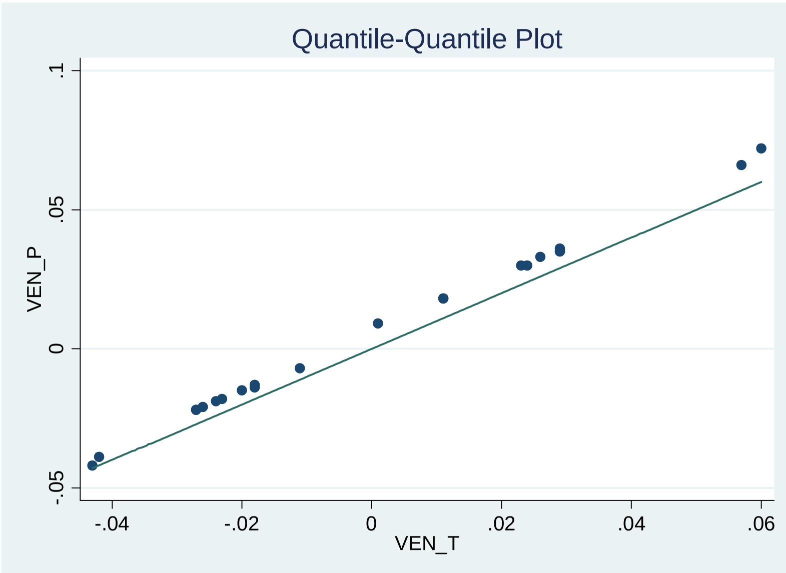
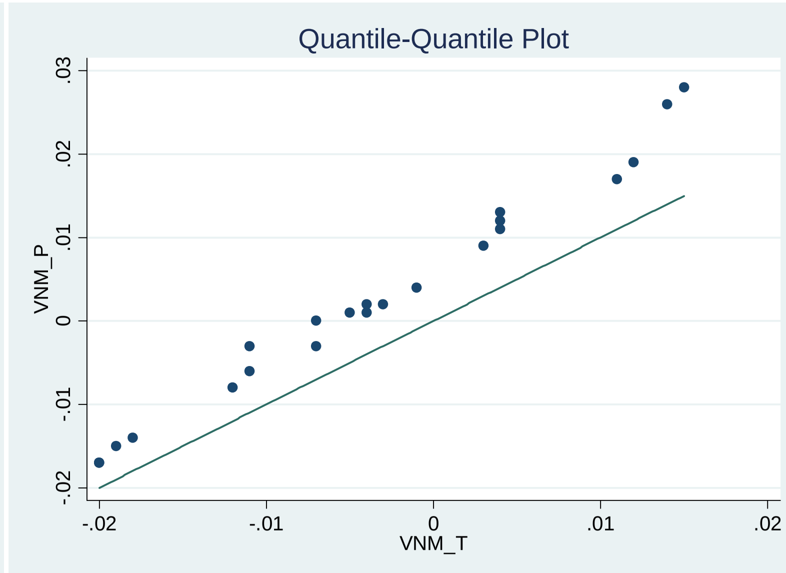
0
.02
.04
.06
.08
-.02
0
.02
.04
.06
.08
MWI_T



Quantile-Quantile Plot
PER_P
PER_T
.06
.04
.02
0
-.02
-.04
-.04
-.02
0
.02
.04
Quantile-Quantile Plot
PHL_P
PHL_T
.4
.2
0
-.2
-.4
-.6
-.6
-.4
-.2
0
.2
.4
Quantile-Quantile Plot
THA_P
THA_T
.01
.005
0
-.005
-.01
-.015
-.015
-.01
-.005
0
.005
Quantile-Quantile Plot
UGA_P
UGA_T
0
-.1
-.2
-.3
-.4
-.5
-.4
-.3
-.2
-.1
0


Quantile-Quantile Plot
VEN_P
.1
.05
0
-.05
-.04
-.02
0
.02
.04
.06
VEN_T


Quantile-Quantile Plot
VNM_P
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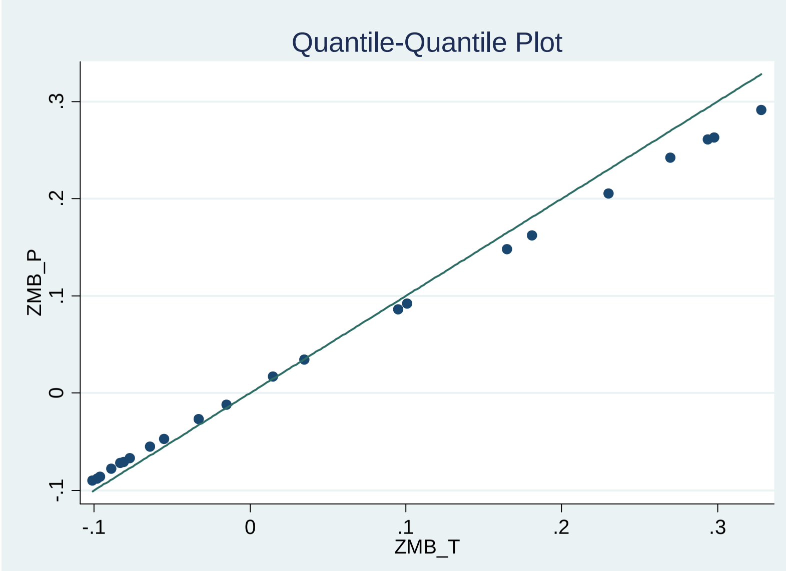
.02
.01
0
-.01
-.02
-.02
-.01
0
.01
.02
VNM_T


Quantile-Quantile Plot
ZMB_P
.3
.2
.1
0
-.1
-.1
0
.1
.2
.3
ZMB_T