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Introducing medium-and long-term productivity responses in Aglink-Cosimo

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Abstract

This report aims at enhancing the Aglink-Cosimo model by incorporating agricultural productivity growth. It contains a first attempt to develop a measure of the productivity response of agricultural commodities represented in Aglink-Cosimo. In the same spirit as Griliches (1963), this work takes into account the role that specific input changes have on explaining medium- and long-term productivity responses.

Aglink-Cosimo model is a partial equilibrium model used to analyse the short to medium term development of annual supply, demand, and prices for the main agricultural commodities produced and traded worldwide. The model improvements described in this technical report aim at capturing endogenously shifts in commodity productivity growth.

In the report we first present how productivity growth is considered at present in the model. Subsequently, we review the literature on how technical progress and price elasticities of yield relate to yield growth. From the literature, we extract a way of capturing endogenously productivity growth. We document the Aglink-Cosimo model changes and focus on some specific cases. Finally, we prepare a scenario analysis on the actual baseline and on an economy with a higher GDP growth rate. The scenario, applied to both cases, studies the effect of a 20% labour price increase on endogenous productivity growth.

In this report, we present several findings relevant to the Aglink-Cosimo community. First, inelastic Aglink-Cosimo crop yields used for the ten-year period commonly simulated by this model are not consistent with indications in the literature of greater long-run response. The relevant literature suggests that yields will be more responsive to sustained changes in price levels if given time for all reactions of crop supply, certainly including farm input supplier investment decisions as well as on-farm adjustments, than if assessed using responses to annual price variations alone. Second, Aglink-Cosimo users can exploit relationships we develop between the economic development of a country, input composition, and yield elasticity. These relationships can be used to calculate long-run yield elasticities for the model. Moreover, these relationships can be built into a set of equations that can help prepare Aglink-Cosimo for long-run projections. Long-run projections predicated on decades of economic growth imply fundamental changes to the agricultural sector. Thanks to the relationships we define here, the implications of development for crop input price indices and crop yield elasticities can now be taken into account. Our third finding is that long-run crop yield response can be successfully introduced to the model. We adjust existing yield elasticities by adding long-run returns to crop production and long-run responses to these returns. We tie key parameters to the level of economic development. The final, successful simulations of this report use a version of Aglink-Cosimo with these revisions. While we do not at this time project far into the future, our simulations show how the relevant literature and available data can be used as the basis for long-run analysis with Aglink-Cosimo.

1 Introduction

This report aims at enhancing the Aglink-Cosimo model by incorporating agricultural productivity growth. It contains a first attempt to develop a measure of the productivity response of agricultural commodities represented in Aglink-Cosimo. In the same spirit as Griliches (1963), this work takes into account the role that specific input changes have on explaining medium- and long-term productivity responses.

The Aglink-Cosimo model is a partial equilibrium model used to simulate development of annual supply, demand and prices for the main agricultural commodities produced and traded worldwide. It is recursive-dynamic model, because current economic decisions are reached by taking into account lagged information on prices and quantities. The model typically solves over a ten-year, forward-looking period, so key measures of productivity are intended to respond to prices in a manner that is consistent with this time frame. With this model improvement, shifts in productivity deriving on output from input aggregate costs' composition should be endogenously captured.

The report is organized into the following sections. Section 2 includes a literature review on agricultural productivity. Section 3 documents the changes done to the Aglink-Cosimo model in order to analyse productivity in agriculture. Section 4 analyses long-run elasticities in selected commodities in Aglink-Cosimo. In section 5 a test policy scenario using the modified model is presented. Conclusions are briefly summarized in the last section. We provide an appendix with a sample of the model changes.

2 Literature review

2.1 Background

The equations in the Aglink-Cosimo model that are used to project crop yields express the logarithm of production per unit of land area as a linear function of the logarithm of a producer incentive price and a time trend.

1) $Log(Y) = a + b * Log(EP/C) + c * T$

Where:

$Y = Yield\ per\ unit\ land\ area$

$EP = Expected\ producer\ price$

$C = Index\ of\ cost\ of\ production\ inputs$

$T = Time\ trend, the\ value\ of\ which\ is\ incremented\ by\ 1.0\ each\ year$

$a = constant$

$b = price\ elasticity\ of\ yield\ response$

$c = the\ annual\ percent\ increase\ in\ yield$

Equation 1 is a simplified version of an actual yield equation used in the Aglink-Cosimo model framework, adapted here for expositional convenience. Later, we consider specific definitions of the expected price and cost indexes. Note that changes in the producer incentive price change the inducement to use more or less inputs per unit land area. Changes in the trend variable boost annual yields by a given percentage, independent of the level of factor use. Moreover, the yield elasticity is constant in all years, no matter how much a country's economy might evolve during the period, and this elasticity with respect to currently expected prices is typically in the range of 0.0 to 0.2 in the model, without allowing for any greater response even for a large and sustained change in real prices.

2.2 Technical progress and yield growth

The question of how much of observed growth in economic output should be attributed to intensification of factor use versus growth in total factor productivity (TFP) has fostered debate amongst economists at least since the publication of an important analysis by Solow (1957). His study focused on the relative contributions of technical change versus capital intensification to the growth in US total output per man-hour during the period 1909-1949. He concluded that nearly all of that growth was attributable to technical change – a finding supported by a large body of subsequent research.

Jorgenson and Griliches (1967) report findings from their research essentially reversing the conclusions from those earlier studies. They found that after correcting for errors in the data and using better methods for aggregating inputs and outputs, growth in total quantities of input use explain the lion's share of growth in total output leaving the role to be assigned to growth in technical progress relatively small.

In an influential study, Griliches (1963) analysed the sources of productivity growth focusing specifically on US agriculture. He found that after correcting for changes in the quality of inputs, refining methods of data aggregation, and accounting for economies of scale, most all of the growth in output over the period 1940-60 was due to growth in aggregate input use, not technical change *per se*. He qualified his conclusions however in noting that his *"…accounting for the observed productivity increases does not mean that there were no meaningful increases in agricultural productivity over this period…rather that we may have succeeded in providing an explanation for what were previously unexplained increases in farm output." (p. 346)*

Agricultural productivity growth has been the target of much research in the years since publication of the Griliches (1963) study. In recent years attention focused on whether we are witnessing a slowdown in productivity. The topic is dealt with in some depth in Wang, Heisey, Schimmelpfennig and Ball (2015). Using data from a USDA-ERS database[1] they also emphasized the importance of taking full account of input quality change when measuring TFP growth. Their method recognizes quality changes over time in land, labour, machinery capital, agricultural chemicals and other factors. The estimated results show that from 1990 to 2010 aggregate input use in US agriculture changed hardly all, leaving the roughly 1.3% annual growth in output over those years attributable entirely to TFP growth. Moreover, they find no evidence of a slowdown in TFP growth.

Fuglie and Wang (2012), employing similar methods and data sources as the Wang et al study mentioned above, summarize findings from their study of productivity growth in global agriculture. They find that in developing countries, as in the US in earlier epochs, increases in total factor use are more important, with TFP growth accounting for only about one third of the near tripling of world agricultural output over the entire period 1961 to 2009. However, they note that productivity in the developing world has steadily grown in recent years with rates of TFP growth in the two most recent decades for which data are available approaching those of the developed world.

Matthews (2014) reports findings from analysis of TFP growth in the EU done by the Directorate-General for Agriculture and Rural Development (DG AGRI) using data from internal sources. Those data cover only the years, 1995-2011. The DG AGRI estimates show a much slower rate of agricultural productivity growth in many of the same EU countries as covered in the Fuglie and Wang (2012 a, b) reports. Matthews notes that explaining these differences constitutes an important item for future analysis.

Total factor productivity is of course not the same as yield - the variable of most immediate concern here. Nonetheless, in terms of aggregate agricultural production, they should be nearly the same. This is because in most countries the quantity of land used in all of agriculture has changed very little over the recent past. The total area used for crops in both North America and in Europe is actually less now than in 1990.

What does this all mean for the trend coefficients in the Aglink-Cosimo yield equations? A quick read of the coefficient files shows that most of the existing estimates of trend coefficients (c) cluster around 0.015, implying a trend growth rate of 1.5%. Indeed, a goodly number of those coefficients appear to have been set at exactly 1.5%. And, again a quick read of estimated rates of TFP growth rates for all of agriculture for individual countries reported in the USDA-ERS database seem to cluster around that same figure. There is considerable year-to-year variation in TFP estimates mainly attributable to weather related events. Accordingly, it is probably safer to focus on average growth rates over a longish numbers of years.

What drives TFP growth? Wang et al. emphasize the role of *"… innovation that results from research funded by both public and private sectors."* There is much empirical research to back up that claim. (see Pardey and Alston (2010); Alston, Beddow and Pardey (2009); Alston, Anderson, James and Pardey (2010 and 2011) and Hurley, Rao and Pardey (2014) for reviews of past analysis and findings from more recent study). Those studies include variables representing various kinds of spending on agricultural research and extension services with alternative lagged structures. An important

[1] The USDA-ERS website http://www.ers.usda.gov/data-products/international-agricultural-productivity.aspx provides links to EXCEL files containing the metadata and TFP estimates for individual countries and regions. Those files contain as well all of the input, output and factor share data used in making the TFP calculations.

conclusion emerging from this literature is that lags between investment in agricultural research and implementation of the fruits of that research are long. Huffman and Evenson (2006) estimate public agricultural R&D has impacts with lags up to 35 years; Alston et al. (2010) estimate lags up to 50 years.

Importantly, in the present context, this leaves little role for changes in relative prices as a driver of technical change in the short to medium run. That is to say, it seems that total factor productivity growth, and by implication, yield trend variables and coefficients might safely be assumed to be exogenous for medium-term projections of the sort typically undertaken using the Aglink-Cosimo model. Of course, price induced changes in the level and composition of input use can affect yields in the short- and medium-run, even when the underlying production technology is changing more slowly.

Two conclusions emerge from comparing existing yield trend coefficient estimates with TFP estimates. First, the TFP estimates could provide a useful check when choosing the Aglink-Cosimo parameters. Yield trend coefficients that are much larger or smaller than TFP estimates would warrant a second look. This does not mean of course that the TFP estimates should provide the sole basis for choosing the precise numerical values of model parameters.[2] There are many reasons to expect that individual crop yield trends would not exactly match TFP trends. Secondly, there seems little basis for questioning the way the trend variables enter the yield equations since there is little evidence to suggest that productivity growth is either slowing or accelerating. And, there seems no need to worry that relative price movement in the short to medium term would materially affect time trend coefficients.

Left unsaid here though is the degree to which technical change has been factor biased and, if so, how to handle it in Aglink-Cosimo. The data in, e.g., the USDA-ERS database show that, in most countries the factor shares for farm supplied labour have declined, offset by increased shares for purchased inputs. But, how much of that is due to technical change and how much due to relative price and wage movements is an open question. Whatever their source, however, secular trends in factor shares can affect both the elasticity of yield response to price and the values of cost indexes used in the Aglink-Cosimo model. We return to this issue later in the report.

2.3 Price elasticities of yield response

Spurred by concern about the environmental effects of agriculture, and of biofuels policy specifically, economists are showing renewed interest in the price elasticity of yield response. And, as Keeney and Hertel (2008) noted, the recent literature is highly polarized. At one extreme, are research findings interpreted to show that yields are determined solely by weather related events and exogenous technical progress (Roberts and Schlenker, 2008; Roberts and Schlenker, 2013). At the other extreme are research findings that imply a more pronounced role for prices with long-run elasticities greater than two (Haile, Kalkuhl and von Braun, 2015).

Yield response to changes in price incentives can be measured at multiple levels, from individual farmer behaviour to sector level responses in countries and regions. When measured using farm level observations, yield price elasticities are typically smaller than when measured using sector aggregates. Hertel, Stiegert and Vroomen, (1996) explain this disparity by observing that sector aggregates reveal both individual farmer responses as well as changes in the composition of the population of farmers responding to price signals. They found that significant yield response develops through price-induced growth in farm sizes by the most efficient managers. Given the sector level orientation of the Aglink-Cosimo model, here we will consider only those studies using aggregate data.

[2] It might be possible however to use the various data aggregates published in the USDA-ERS database to estimate a TFP more specific to the crops subsector by, e.g., dropping livestock outputs and livestock specific inputs from the respective indexes.

One approach to modelling yield response to price calls for specifying a production function and the associated factor demand and supply equations and then choosing plausible elasticities of factor substitution and supply from the literature. This approach has a long history in agricultural economics dating back to an analysis of the factor implications of farm support policies by Floyd (1965).

In a highly influential textbook on the economics of agricultural policy, Gardner (1988) refined and extended Floyd's model to examine a wider range of US agricultural policies and markets. The approach was extended further in Hertel (1989) and in Gunter, Jeong and White (1996) and applied to analysis of agricultural trade. The specification of OECD's multi-country policy evaluation model – the PEM (OECD, 2001; Martini, 2011) follows closely Gardner's US version.

Supply and yield elasticities in this category of models are implicit. Gardner (1988) derives expressions for the elasticity of supply in the two-factor case. His formulation makes clear how the supply elasticity depends on factor shares and assumed values of factor supply and substitution elasticities. Hertel (1989) generalizes the Gardner derivation to cover multi-factor production functions.

Keeney and Hertel (2008) start with the Hertel (1989) formula for the supply elasticity and then invoke the assumption of a fixed allocation of land, i.e., a zero price elasticity of land supply to obtain an expression for yield price response. The assumption of a zero price elasticity of land supply for purposes of modelling yield response is usually justified by appeal to the notion that area allocation decisions are pre-determined relative to decisions about how much and in what combinations factors affecting yield are made. We defer, to a later section, further discussion of yield elasticities obtained from this approach to modelling.

Another way of modelling yield response to prices is to use yield response equations such as Equation 1 in which yield price elasticities are explicit. Numerical values for these explicit elasticities are also typically chosen from the literature. This is the way yield is modelled in most multi-country, multi-product models: FAPRI model (FAPRI-MU, 2004); the ERS/Penn State Trade Model (Stout and Abler, 2004); the EU's CAPRI model (Adenäuer, 2008; Witzke, 2005) and IFPRI's WATSIM model, Kuhn (2003).

The literature offers a set of directly estimated yield elasticities richer than factor supply and substitution elasticities needed for the first category of models. In general, yield elasticities implicit in first category of models are greater than directly estimated ones. The comparison of the PEM and Aglink-Cosimo yield elasticities in Table 1 below illustrates the point.

Table 1. Comparing crop yield elasticities in Aglink-Cosimo and OECD PEM

	Maize	**Wheat**	**Soybean**
EU:			
Aglink-Cosimo	0.05	0.07	0.03
PEM	0.71	0.75	0.67
USA:			
Aglink-Cosimo	0.06	0.02	0.20
PEM	0.65	0.67	0.53

Note: PEM yield elasticities calculated using the formula derived in Keeney & Hertel (2008). See Equation 3 below.

The PEM elasticities are orders of magnitude greater than the Aglink-Cosimo elasticities. This is probably because the latter are relative to yearly price-yield elasticities while the former evaluate price-yield response after a five-year adjustment period. Moreover, as will be seen subsequently, the Aglink-Cosimo elasticities are considerably smaller even than most available estimates of yield elasticities reported in the recent literature. At the same time, the PEM elasticities are considerably larger than most estimates reported in the literature (Keeney and Hertel, 2008).

2.3.1 Issues in estimating and interpreting yield elasticities

Most past estimates of yield price response use exclusively, or mainly, annual time series data. However, weather shocks and trend yield growth are usually way more important determinants of the year-to-year variation in yields than is the relatively modest, annual variation in output and factor prices. These non-price factors so dominate that it becomes difficult to isolate a price response econometrically. This potential for large weather impacts on year-to-year yield variation as compared to modest short-run response to prices can cause statistically insignificant price coefficients when yields are subject to regression analysis. Statistical significance is not the same as economic significance, however, and these challenges to regression analysis need not justify zero short-run response, let alone zero long-run response, as discussed below.

Schlenker and Roberts (2008) estimate the effects of weather variation on wheat, soybean and cotton yields using annual data for the period 1950-2005. They supplement their estimated impacts of weather on yield with estimates of the impact of weather on futures prices but without testing if prices can, in turn, affect yields. They find that weather induced yield reductions are large – a third or even more than a half – and yet do not note that the consequent price impacts might have some effect on yields over the time period in which climate changes.

Roberts and Schlenker (2013) also assume that annual yield variation is determined exclusively by weather shocks, arguing that weather and the resultant shocks to yields are both purely exogenous to market conditions. They invoke this assumption in an effort to deal with another problem plaguing regression analysis - simultaneous equation bias. Typically, the price variable used in yield equations is endogenous to yield variation and thus affected simultaneously with yield impacts due to exogenous weather or other shocks. If not corrected, simultaneous equation bias can add to downward bias in estimated supply elasticities (Roberts and Schlenker, 2013).

One method econometricians use to correct for simultaneous equation bias is to choose instrumental variables to be included in the analysis whose effect on yields is purely exogenous. The difficulty arises in finding such variables. Goodwin, Marra, Piggott and Mueller (2012) point out that, while the arguments in favour of the need for exogenous instrumental variables is undeniable, the specific choices applied in practice may not always offer advantages over simply ignoring the problem (as they seem to do in their own analysis).

In commenting on the Roberts and Schlenker analysis, Goodwin et al. (2012), observe that, while weather shocks can safely be regarded as exogenous, the assumption that the effects on yields is also exogenous is open to debate. If weather shocks lead to changes in expected market prices then it seems doubtful that producers would not respond to those changed prices by altering input combinations affecting yield.

Just and Weninger (1999) argue that non-normality of crop yields, aggregation, and equation specification pose interrelated challenges in estimating yield response functions. They point specifically to challenges posed in choosing the order of the trend term and heteroscedasticity in the data. Even though Just and Weninger ignore price incentives, their work suggests that any effort to estimate directly the sensitivity of yield to economic variables is likely to be complicated. Subsequent research in this area highlights other challenges of direct estimation, including testing over other distributions, autocorrelation, aggregation, changing parameters, and over-fitting (e.g. Annan et al., 2013; Claasen and Just, 2010; Koundouri and Kourogenis, 2011; Shaik et al., 2008; Ye and Babcock, 2010; Zhu et al., 2011). One trait that seems shared among all these efforts at identifying the shape of the yield distribution, with whatever nuances such as trend estimation or aggregation, is the absence of economic incentives. Price is apparently not included as a potential explanatory variable.

A further problem potentially biasing downwards econometric estimates of yield response elasticities relates to the distinction between actual and expected prices. Peterson (1988) makes the case that time series estimates of yield response understate the true response to expected price changes because much of the observed price variation is transitory, causing actual prices to vary more than expected prices. He worried specifically that agricultural price policies based on relatively small estimated elasticities run the risk of underestimating their impact on output because policy changes tend to influence long-run expected prices.

Peterson defends an approach using cross-country observations because yield differences among countries should better reflect responses to stable differences in average levels of expected prices. Haile, Kalkuhl and von Braun (2015) combine annual and cross-country data in their analysis of worldwide yield response. Haile et al. include both lagged yield and lagged prices as regressors in the estimating equations. Results obtained from these lagged adjustment type equations enable calculation of elasticities for different lengths of run. The implied long-run elasticities of yield response in lagged adjustment models are often significantly greater than are the short-run responses.

Other recent studies similarly pool time series of annual observations with cross-sectional observations. Goodwin, et al. (2012) use crop reporting district aggregates for three US states: Indiana, Iowa, and Illinois. Analyses reported in the Huang and Khanna (2015) and the Miao, Khanna and Huang (2015) pool US county level cross-sectional and time series data.

In none of these latter cases however does it seem likely that actual or expected market prices would differ meaningfully across the panel dimension of the data, leaving most of the observed price variation due to evolution of prices over the time series. Many past regression analyses of yield response to price relied exclusively on time series of annual observations. This means that the price yield elasticities obtained in all these studies should be interpreted as short run, year-to-year, responses to price. In cases where the expected price is represented by an average of past prices, the induced yield response would last for as long as is the length of lag used in the average. In the literature reviewed in this report, including the more recent studies mentioned above, expected price in yield equations has been represented either by a one year lagged price, a current year price or a current year futures price quote.

However, a change in expected prices in a particular year would normally be expected to engender changes in factor combinations that play out over several future growing seasons. An especially illuminating example of this distinction between short- and long-run responses is that of farmer's choices of seeds to plant in response to, e.g., higher commodity prices. In the short run those choices are of course limited to 'already on the shelf' varieties. And, undoubtedly, there are some alternatives even among those choices – for different lengths of growing season and across a range of prices. But, there is also a longer run response as seed supplying companies, responding to higher commodity prices expand their R&D budgets in order to bring new varieties to market.

Farmer's decisions to invest in new equipment in any given year may reflect changes in expected prices formed in that year but with consequences that play out over the productive life of that equipment. Changes in hired labour can occur within shorter spans of time but family labour, whether via reallocations or via entry and exit into farming, may change only very slowly. Even pre-existing patterns of fertilizer and agricultural chemical applications and other production practices may persist over more than one or two seasons after a change in expected prices.

Consider the following expression for the elasticity of yield response adopted from Gardner (1988):

2) $$\frac{EY}{EP} = [e_a e_b + \sigma(K_a e_a + K_b e_b)]/(\sigma + K_a e_b + K_b e_a)$$

where:

$\frac{EY}{EP} = percent\ change\ in\ yield\ for\ a\ given\ percent\ change\ in\ expected\ price$

$e_a = elasticity\ of\ supply\ of\ input\ a\ used\ per\ unit\ of\ land\ area$

$e_b = elasticity\ of\ supply\ of\ input\ b\ used\ per\ unit\ of\ land\ area$

$\sigma = elasticity\ \ of\ factor\ substitution\ between\ factors\ a\ and\ b$

$K_a = share\ in\ total\ cost\ of\ production\ of\ factor\ a$

$K_b = share\ in\ total\ cost\ of\ production\ of\ factor\ b$

Let factor '*a*' refer to an aggregate of quasi-fixed factors exhibiting low supply elasticities and factor '*b*' to an aggregate of variable factors exhibiting high supply elasticities. We might imagine, for example, machinery and equipment fitting into the first group; fertilizers into the second. Notice now that the higher is the share of quasi-fixed factors in the mix, K_a, and the lower is the corresponding elasticity, e_a, the lower is the yield price elasticity. Parallel reasoning leads to the opposite conclusion for the variable factors.

But, which factors can be considered quasi-fixed and which ones variable is time dependent! Given a one year adjustment horizon, many inputs would be considered quasi-fixed. Given a ten-year adjustment horizon, most might be considered variable.

Thus, yield response elasticities that are estimated using only annual time series data, including those combining time series and panel data but where most of the variation is due to year-to-year variation, may seriously understate long-run response. Moreover, and of specific concern for Aglink-Cosimo yield equations, it is probably inappropriate to use time-constant yield elasticities for multi-year projections.

The above discussion points to three challenges confronting econometric estimation and interpretation of yield elasticities: 1) the low signal to noise ratios in the price and cost data, 2) the identification problem and 3) the time dependent nature of yield response. Taken together these lead to the suspicion that many of the yield elasticities reported in the literature could understate true response elasticities, at the least for medium to longer-term policy concerns.

2.3.2 Recent estimates of price yield elasticities

Keeney and Hertel (2008) report findings from their extensive review of past studies of yield response to prices, focusing mainly on US crops. Their review is notable both for its breadth of coverage of the literature and for the method they use in an attempt to synthesize past thinking on the subject. Nevertheless, findings are highly diverse providing little guidance for choosing specific numerical estimates of yield response for any commodity other than for corn in the US. They concluded that there seems little prospect for reconciling the diverse estimates for any of the other crops.

For corn, they settle on a long-run (3-5 years) yield price elasticity of 0.25. That estimate they subsequently adopt in analysis of biofuels policy (Keeney and Hertel, 2009).

However, Berry (2011) was sharply critical of that choice. His assessment of yield elasticity estimates reported in the literature supports a yield price elasticity of no greater than 0.10. He accuses Keeney and Hertel of choosing the higher value of 0.25, not based on consensus findings from the literature[3] but because of "…a strong *a priori* belief that yield elasticities should be set to a fairly high level regardless of the actual findings of the empirical literature", p.2

Berry further criticizes the Keeney and Hertel (2009) analysis noting that most of the studies included in their review are somewhat dated. This concern in echoed in the Goodwin et al., (2012) paper. They highlight how the economic environment for farmers changed quite dramatically with important changes in US agricultural policy occurring in the US in 1996 and restrict their regression analysis to the years after that change. The same concern would apply to analyses of data for the EU countries following major policy reforms in the 1990's. None of the econometric analyses reviewed in Keeney and Hertel (2008) used data whose ranges extended to 1996; only very few whose data ranges extended into the 1980's. Accordingly, here, the main focus of attention will be studies using more recent data. Moreover, I restrict attention only to those studies that report attempts to estimate yield elasticities thereby ignoring those using assumed estimates. Table 2 below contains the findings.

The Peterson (1988) analysis proceeded in two steps. In the first step he estimated a Cobb-Douglas production function relating total agricultural output, expressed in wheat equivalents, to four inputs: labour, machinery, fertilizer and livestock. He used three year averages (1982-84) of quantities for these inputs and for output. He then took the estimated results and derived implicit factor prices based in the first order conditions requiring equivalence between the value marginal product and the factor prices. These he uses in the second step of his procedure to estimate the yield elasticities as a function of the ratio of output price to a share weighted index of the implicit factor prices.

[3] In fact, Keeney and Hertel arrived at the 0.25 estimate from simulations they did with the PEM. They justified that choice based on their reading of empirical results reported in the literature.

Table 2. Estimated elasticities of crop yield response to output price

Source	Region	Data	Estimate
Peterson, 1988			
All crops	Multi-country	Cross-section, 119 countries	1.19 (Long run)
Guyomard et al., 1995:	France	Annual time series 1970-92	(Short run)
Other coarse grains			0.22
Soft wheat			0.39
Maize			0.31
Barley			0.35
Rapeseed			0.22
Sunflower			0.17
Soya			2.85
Arnade and Kelch, 2007	**US state of Iowa**	**Annual time series 1960-99**	**(Short run)**
Corn			0.195
Soy			0.258
Other grains			0.444
Rosas et al., 2010	**US state of Iowa**	**Annual time series 1960-04, Results from agronomic field experiments**	**(Short run)**
Corn			0.29
Soybean			0.61
Huang and Khanna, 2010	**US**	**Annual time series 1977-07** **Cross-section of US counties**	**(Short run)**
Corn			0.15
Soybean			0.06
Wheat			0.43
Goodwin, et al., 2012	**US States of Iowa, Indiana, Illinois**	**Annual time series 1996-10** **Cross-section of the 3 states**	**(Short run: inter + intra seasonal response)**
Corn (time series + cross section)			0.2014 to 0.2819
Iowa			0.2891
Indiana			0.1610
Illinois			0.4361
Miao, et al., 2015	**US**	**Annual time series 1977-07** **Cross-section of US counties**	**(Short run)**
Corn			0.23
Soybeans			0.00
Haile et al., 2015	**Multi-country**	**Annual time series 1961-2010** **Cross-section of 32 countries**	**Short run SR & Long Run LR**
Wheat			0.166 (SR) 2.075 (LR)
Corn			0.094 (SR) 2.350 (LR)
Soybeans			0.146 (SR) 1.947 (LR)
Rice			0.043 (SR) 0.1558 (LR)

The dataset comprises a cross-section of observations for 119 countries. He observed that the average value of his constructed price index for the ten highest countries was twenty times the average for the lowest ten. To the extent that such differences are stable through time, it bolsters his case that the yield elasticity that he estimates should be viewed as response in the long run.

Guyomard, Baudry and Carpentier (1996) derive their estimating equations from a multi-output, multi-input profit function. They use the resulting model to analyse EU policy reforms that featured a significant reduction in price support offset by an increase in area payments. The policy question was whether this constituted a sufficient reduction in price incentives to reduce yields. They concluded that the reduced price support levels did indeed lead to significant reductions in yields.

Arnade and Kelch (2007) also employ a profit function to obtain equations representing producer land allocation and yield decisions, enabling separate estimates of area response and yield elasticities. Interestingly, their estimated yield elasticities are significantly greater than the area response elasticities. Similarly, both the Guyomard et al., and the Haile et al., analyses find estimated price elasticities of yield response significantly higher than those for area response for most of the crops studied. Such findings stand in sharp contrast to an assertion made by Berry (2011 *p.8.*), that *"There is a long tradition in agricultural economics … that takes as obvious that almost all of the price-elasticity of supply comes from land-use rather than yield."*

Rosas, Hayes and Lence (2012) use a highly innovative method to estimate crop yield elasticities that combines market-based datasets with data from agronomic field tests. They specify a production function to exploit the experimental data and, independently, derive output supply and factor demand equations from a profit maximization function and duality theory. Some of the parameters appearing in the production function are the same as in the equations derived from duality theory. Their procedure exploits this by imposing constraints that allow them to simultaneously estimate the same parameters from the two different models.

The inclusion of outside information was meant to help overcome the identification problem that plagues application of duality theory alone in empirical work. The yield elasticities they obtain using the mixed method are notably higher than those obtained when using the dual method (0.29 vs 0.17 for corn; 0.61 vs 0.45 for soybeans).

Huang and Khanna (2010) estimate yield elasticities using single regression equations expressing yields as a function of one-year lagged price, weather, technology and land quality variables. Data on yields, weather and land quality variables are county specific. However, price data is only specific at the state level. Similar to results in some other studies, Huang and Khanna find that choice of time trend variable (linear or quadratic) does lead to some differences in estimated price elasticities.

Most analyses of yield response acknowledge only the possibility of a year-to-year, or inter-seasonal, adjustment to price incentives. Goodwin et al. consider those types of responses plus the possibility that farmers may alter input choices in response to price changes within a single growing season, i.e., intra-seasonal responses. In defending their approach they note that the range of input choices available to farmers is much greater today than in the past, mentioning specifically genetically modified seed.

They indeed find intra-seasonal yield price elasticities that are statistically significant though relatively small compared to inter-seasonal elasticities. Such findings bolster support for the more general assertion that yield response to price changes will naturally be greater the longer the period of adjustment. If inter-seasonal response is greater than intra-seasonal, surely then a two-year response would be greater than a one-year; a three-year response greater still and so on.

Miao, Khanna, and Huang (2015) estimate corn and soybean yield equations for the United States using a panel dataset comprising county level observations for the 1977–2007 period. As in the similarly structured Khanna and Huang study the data for yield and for various indicators of weather is county specific. However, price and cost data is only specific at the state level. They use instrumental variables to control for endogeneity of prices. They estimate a yield to corn price coefficient that is statistically significant but the effect of soybean price on soybean yields is not statistically significant.

The Haile et al. analysis reports estimation results making it possible to calculate yield response for differing lengths of run, although the authors seem shy about doing so, reporting only short run elasticities in the text. Their regression equations include, besides a one-year lagged price, a lagged dependent variable and indicators of price variability. They use an international rather than a domestic price. This means that the elasticities they estimate reflect both a world to domestic price transmission effect and a yield response effect. Considering that the world to domestic price transmission elasticity would be less than 1.0 for most countries in their sample, the true domestic yield to domestic price elasticities could be significantly greater than the ones they obtain.

The sampling of recent studies of yield price response summarized in Table 2 and discussed above does not contain the needed country or commodity coverage to draw a consensus view to carry forward to Aglink-Cosimo. Nonetheless, it does lead to some potentially useful insights for that purpose. First, the yield to price elasticities in the model now are, for the most part, significantly less than findings from recent studies. And, this, despite the fact that almost all of the more recent estimates should be viewed as short-term elasticities. The two studies from which long run responses can be inferred provide evidence of still much higher yield elasticities. [4]

2.3.3 A proposed approach for Aglink-Cosimo yield equations

There are two challenges to be overcome in introducing medium to long-term yield price elasticities in the Aglink-Cosimo model. The first is how to choose numerical values for them; the second, how to change the specification of the equations. A good option for the first challenge is to use the yield elasticity formula that Keeney and Hertel (2008) derived for their analysis.

$$3)\ E_{Y,LR} = \left\{ -[1\ 1\ 1] \times \begin{bmatrix} \partial_{1,1} - n_1/c_1 & \partial_{1,2} & \partial_{1,3} \\ \partial_{1,2} & \partial_{2,2} - n_2/c_2 & \partial_{2,3} \\ \partial_{1,3} & \partial_{2,3} & \partial_{3,3} - n_3/c_3 \end{bmatrix}^{-1} \times \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \right\}^{-1}$$

where:

$\partial_{i,j}$ are elasticities of factor substitution for, in this case, three production factors, e.g., land, farm-owned and purchased. (The matrix is symmetric.)

n_i are factor supply elasticities,

and c_i are cost shares.

Equation 3 is in fact the expression for the elasticity of *supply*. Following Keeney and Hertel (2008) it can be used to represent the price elasticity of yield by setting the land supply elasticity to zero. Importantly however, notice that doing so does <u>not</u> eliminate land from the equation. Both the cost share of land and the elasticities of substitution between land and the other factors remain as variables in the equation. Importantly, the higher is land’s share, the lower the elasticity of yield response (Sadoulet and de Janvry, 1995, p. 75)

The only problem now is where to get the factor shares and the elasticities of factor substitution and supply? Estimates for these parameters are readily available only for OECD countries covered in the PEM (OECD, 2001). These estimates reflect findings from

[4] Interestingly, the yield elasticities estimated for US corn in those several recent studies all fall in a fairly narrow range that includes the 0.25 Keeney and Hertel (2009) used – even though none of them were available before their publication.

extensive reviews of the literature done for the US, Canada and Mexico by Abler (2001) and for a large number of European countries by Salhofer (2001). Those two reports also present plausible ranges of values for the elasticities of factor supply and substitution. Martini (2011) reports estimates of these parameters obtained in similar fashion for Japan and South Korea.

For other countries however, i.e., the great majority of those in the Aglink-Cosimo, such information is mostly lacking. There are already some cost shares in the model that are used to calculate the input price indexes used as a price deflator in the yield equations and elsewhere in the model. The USDA-ERS international productivity database reports cost shares for aggregate agriculture. The evidence from past studies of elasticities of factor substitution and factor supply response in OECD countries[5] reported in OECD (2001) and Martini (2011) could provide starting points.

Keeney and Hertel (2008) used Equation 3 above to, essentially, consider alternative settings of supply elasticities for farm owned (mainly family labour) and an aggregate of purchased factors. The alternative settings they chose were from the plausible ranges of values reported in Abler (2001). Such an approach could be extended to consider the ranges of plausible values for European countries reported in Salhofer (2001) as well as for other parameters for which plausible ranges were reported in those two studies. The objective would be, as in Keeney and Hertel, to estimate medium-long run yield elasticities for various countries or regions in Aglink-Cosimo that fall in a 'comfort zone'. Estimates could then be refined over time as better parameter estimates become available.

Let us turn now to the other main challenge, that of altering the Aglink-Cosimo equations to represent medium- to long-run yield response. All things considered, the most practical option seems to be to use moving averages of past ratios of price to cost indexes. These could be specified in ways that maintain existing short-run elasticities and that spread out the adjustment from those estimates to targeted long-run elasticities over as many years as seem appropriate.

A simplified version of this type of yield equation is:

$$4)\ Log(Y_t) = a + b * Log\left(\frac{EP_t}{C_t}\right) + (c - b) * Log\left(\sum_{i=1}^{N}\left(\frac{P_{t-i}}{C_{t-i}}\right)/N\right) + d * T$$

Where:

a = intercept,

b = short-run elasticity,

c = long-run elasticity,

N = length of run chosen, and

d = any remaining trend coefficient attached to a trend T.

2.4 Input price indices and factor shares

The structure of the input price indices used in Aglink-Cosimo yield equations seems standard for this type of model. Of course, to the extent that cost share information with greater coverage of inputs could be found to calculate the weights, the incorporation of input price indices seems warranted. As noted above, these parameters can be critically

[5] This review found no studies reporting elasticities of factor supply response for the non-OECD countries featured in the Aglink-Cosimo model.

important, not merely as indicators of input prices but in making the elasticity calculations.

The evolution of the shares themselves poses different challenges. As noted above those shares have certainly changed over time - farm supplied family labour shares generally declining, purchased factor shares, especially for chemical inputs, generally rising. These developments have important policy implications. As already noted, part of this evolution could be attributed to relative price movements, part to non-neutral technical change.

Seater (2000) examines the economy-wide relationship between factor shares and technical change. He points out that there is no particular reason for assuming that technical change alters only total factor productivity. The results of his analysis suggest that factor shares do indeed change as a result of technical change.

In a discussion of the distributional consequences of farm policy, Gardner (1988) addresses the question and develops an expression for the elasticity of factor share with respect to output price. It shows that the lower is the elasticity of supply of a factor the more its share will rise with higher output prices and vice versa. He noted that farm supplied factors, land and family labour, typically exhibit lower elasticities of supply than purchased factors, higher output prices lead to a greater share of extra revenues for these factors when output prices increase. Of course, over the longer term, real farm prices have not been increasing but declining as have factor shares for farm-supplied factors.

However, as practical matter, using Gardner’s formula in empirical applications is problematic for two reasons. First, it too requires assumptions about elasticities of substitution. And, in this case, we cannot so easily get away with Cobb-Douglas assumptions of unitary elasticities of substitution since under those assumptions factor shares are fixed. (See Gardner’s discussion on pages 139-41.) The second problem is conceptual. If we use Equation 3 to estimate long-run elasticities, those estimates will already embody, implicitly, the price induced changes in shares.

The secular decline in the share attributed to farm-supplied labour and the corresponding increase in the shares for inputs purchased off the farm seems a particularly important development to incorporate in Aglink-Cosimo projections. Whether this trend is due to exogenous, factor-biased, technical change or a response to relative price movements is a question for future research. Taking this pair of developments into account would be automatically reflected in the projected annual values of the input price indices. Additional equations would need to be added to the model to take account of the knock-on effects on the crop yield elasticities. That is to say, the yield elasticities themselves would need to be made endogenous in the model. As a first step the corresponding yield elasticity equations could be specified to include only the input price weights of interest.

One approach for acknowledging the long-run cost share trends in Aglink-Cosimo would be to introduce equations that express the input price index weight of farm-supplied labour (proxied by the non-traded factor now in the model) as a function of a trend variable, taking care to choose an appropriate functional form for the relationship and acknowledging that the share for purchased factors would have to be specified as a residual.

Another intriguing possibility arises in observing that the data seem to suggest that the phenomenon of declining farm-labour cost shares is closely related to economic development. The further along a country is on the development path, the lower is both the number of people employed in agriculture and the lower is the cost share for farm-supplied labour.

Thus, as an alternative to using time trend variables to track secular movements in input factor shares applied in the fixed-weight input price index, one could link the evolution of farm-labour shares to some indicator of development. A natural choice would be GDP per capita.

2.5 Some conclusions from the literature

Let us consider in turn the following three questions:

1. *Are the time trend coefficients consistent with available estimates of technical progress in agriculture?*

The answer here is, 'generally speaking', yes. Nonetheless, there may be opportunities to better connect in some way existing estimates of technical progress in agriculture to the Aglink-Cosimo model. That field of research will remain a major focus of policy attention and could offer many possibilities for analysis with Aglink-Cosimo to make additional contributions.

2. *In the light of the theory of production and findings from past studies, do the magnitudes of the price elasticities constitute 'plausible' indicators of yield response to price in the medium to longer term?*

Here, neither the theory nor recent empirical evidence supports a yes answer to this question. Even when interpreted as estimates of the short run elasticity of yield response to price, current Aglink-Cosimo estimates appear unrealistically low as compared to many estimates found in the literature. The disparity becomes even much greater when interpreting them, as they have been until now, as medium- to long-term price elasticities. Adopting the procedures for estimating yield-response elasticities proposed here will lead to significantly higher values. This will show up in medium- and long-term projections and, especially, in the findings from policy analyses undertaken with the model. Indeed, refining the representation of yield response opens up new possibilities for doing analyses of highly topical policy questions, including biofuels policy and the consequences of environmental change.

3. *How might the specification of the equations, the definitions of the price and input price variables and the coefficient values be changed to improve representation of medium- to long-term productivity responses in the Aglink-Cosimo model?*

The report makes some specific suggestions in regard to this objective. In the subsequent text, we report on one application that introduces long run yield response to prices in Aglink-Cosimo. However, like any model development, testing and use must 'vet' new specifications in a variety of contexts that include consideration of the policy implications.

3 Documentation of model changes

3.1 Introduction

The model is changed to introduce long-run crop yield elasticities. The method takes into account how economic development affects input price index weights in yield equations and in particular the share of non-traded inputs as a proxy for labour. Changes to the model to implement the lessons from the literature review follow closely the structure of the input files for the PC-Troll-based version of Aglink-Cosimo. The steps are:

1. define new variables;
2. define new parameters;
3. change definition of existing variables or parameters;
4. assign values to new parameters;
5. calculate intermediate variables;
6. estimate the share of non-traded inputs in non-land costs[6] as a function of GDP per capita over time and introduce it as endogenous variable in the calculation of the cost of production commodity index (CPCI);
7. calculate implication for other (non-labour) weights in the input price index;
8. estimate long-run yield response as a function of the non-traded share of non-land input price indices; and
9. adjust existing yield equations to draw in long-run yield response.

The documentation follows standard Aglink-Cosimo notation. Variables names usually take the following form:

YYY_CC_ZZZ

where YYY is the three-letter code indicating the country or region, CC is the commodity code that is at least two-letters long and ZZZ indicates the quantity, price or other market or policy variables. Two give a few relevant examples, USA_MA_CPCI is United States maize input price (Cost of Production Commodity) index and USA_MA_YLD is United States maize yield. Parameters are defined in an identical manner, but start with the prefix "C.". To facilitate the model changes, this code of practice is treated more as guidelines than actual rules.

3.2 Notes on implementing model changes and concerns

The model revisions are guided by the results of the literature review and by the requirements for use in Aglink-Cosimo. Gross domestic product per person (GDPPC) is taken to be the key indicator of economic development. This variable can already be calculated from macroeconomic assumptions that are already used for model simulations; no new projection data are required. GDPPC evolution is mapped to decreasing non-traded share of non-land input price indices (see section 3.2.2). This effect is tied to the non-traded share of the input price index. Changes in non-traded input share of non-land input price indices determined long-run yield elasticity in the projections. The process of incorporating into the model the lessons learned from the literature, as were stated in the previous section, required certain steps to parameterize key relationships. Certain key judgments or uncertainties are reported in this section.

3.2.1 Representation of input price indices

The non-traded input price index share is assumed mostly to reflect the share of labour in total non-land input price indices. This correspondence is not exact because there

[6] Aglink-Cosimo crop input price indices and associated weights are defined appropriately for the model. For example, the crop input price indices do not include land prices since they are implicitly changing in the area equations. As a result, adding land prices as explicit variables in the input price indices would require both different area elasticities and some mechanism for making land prices endogenous.

might be other input prices reflected in the non-traded input price index share. However, given that energy, fertilizer, seed and traded inputs are represented as individual shares and land is excluded, the usage of non-traded cost share as a proxy for labour input price share seems reasonable. Additional data might allow a more nuanced correspondence.

3.2.2 Linking labour input price data and the effects of economic development

To derive labour cost estimates, we use GTAP data that provide a cross-section of costs. The sum of skilled and unskilled labour is compared to other costs, excluding land, to estimate the share of labour in total non-land costs. However, the role of intermediate inputs in the GTAP data is not entirely clear, and further consideration of this step might be warranted.

World Bank GDP and population data are used to calculate GDPPC. A regression is then used to determine a relationship between GDPPC and labour share of non-land costs. Our hypothesis is that rising GDPPC causes labour share of non-land costs to fall. Although several functional forms are tested and no single choice stands out clearly on statistical grounds, a double-logarithm specification is used because this structure is consistent with many other equations in Aglink-Cosimo and to ensure that the labour input price index weight remains positive.

In principle, there might be additional statistical analysis to determine the parameter governing how GDPPC affects labour input price index weight. For example, while one-way causality from GDPPC to labour share of input price index is consistent with how we use the parameter, more complicated analysis might consider endogeneity bias. Other steps might be to consider more years in the analysis, rather than focus on a cross-section of only one year, or to test for additional functional forms.

Other input weights in the index rise for any reduction in non-traded input share in the model to offset the changes such that all input price still sum to unity. The fact that the weights of the various inputs in the input price index sum to one is required by theory and also can serve practical reasons. For example, if the weights do not sum to one, then the existing crop area and yield equations will no longer exhibit homogeneity of degree zero. In this case, the model would project that a country with equal and pronounced inflation in all prices would have rapidly expanding or declining crop production without any economic basis for this result. However, the adding up condition also entails that any change in the weight of non-tradable goods in the input price index is offset by counteracting changes in the other weights of other inputs.

We assume that other input price index weights rise equally for any reduction in non-traded input price index weight in the model. Thus, a 1% reduction in non-traded input weight causes 0.25% increases in each of the traded, seed, energy, and fertilizer input price index weights. Alternative representations of the evolution in input price index weights could be explored. In any case, a simple assumption is warranted, if possible. First, there was little reason to deviate from the assumption of identical effects, at least at present. Second, if shares changed differently then there would still necessarily be additional changes to make sure that shares sum to one. Nevertheless, this assumption is not entirely satisfactory and the evolution of shares should be watched in model use.

The input price index weights are calibrated to cost shares, but input quantities and cost shares are implicit in Aglink-Cosimo rather than explicitly estimated. One could attempt to restructure the model and estimate cost shares, as well. In practice, this undertaking might be most effective if the input price index weights are not used, but instead a set of new cost variables are generated. If input price weights are endogenous with respect to input or output prices, then there could be problems given the current structure of the model. One can imagine that endogenous input price weights might lead to incorrect results if, for example, an increase in the price of the most expensive input causes a large shift in weights in favour of the cheapest input. In this case, the increase in the price of one input can lower the total input price index because of the change in weights and, consequently, increases output.

Although other models have been used to explore vertical markets, including the PEM and GTAP models from which we draw relevant information for the present exercise, Aglink-Cosimo is not designed to estimate explicitly total crop costs, non-land input quantities, and cost shares.

Changes in input quantities and cost shares are implicit in Aglink-Cosimo. The yield and area responses to a change in an input price, with or without the changes to long-run yield elasticity of this report, can include some substitution among non-land inputs. However, because these quantities and markets are not represented explicitly in the model, they are not observed.

The equations suggested here respect the definition of the input price index and does not attempt to redefine the input price index weights as cost shares. The changes introduce the implications of long-run economic development by allowing input price index weights to evolve over time as functions of an indicator of economic development that is exogenous, not determined elsewhere in the model. This method successfully recreates the observed changes in the structure of agriculture as countries develop, and specifically the declining weight of labour in the input mix.

The suggested changes also create opportunities to extend this work in order to include additional effects. Although the changes wrought here seem appropriate given the relevant literature and appropriate data, the method could in principle be applied to other input weights, instead of labour. Given appropriate data, the method could be used to estimate differences in the evolution of all weights, rather than focusing on one as an indicator that is then used to drive other weights. The representation includes trend terms in yield equations, allowing modellers to introduce additional effects on total factor productivity as it relates to yield. The prices used as proxy for crop input prices could also be adjusted if necessary. For example, the GDP deflator is retained as the indicator of the non-traded (labour) price, as in the original model, but better data might be available. Even without time series data, a systematic difference in the trend of GDP deflator and the price of labour to crop production could be reflected by adjusting this term. Thus, this representation can be extended to include additional effects with modest adjustments to the yield trend or to one of the input prices.

3.2.3 Linking non-traded input price index weight to long-run yield response

The literature review and the objectives of the project lead us to estimate long-run yield response as a function of the non-traded weight in the non-land input price index.

Table 3. Ranges of parameters for developing links from shares to elasticities

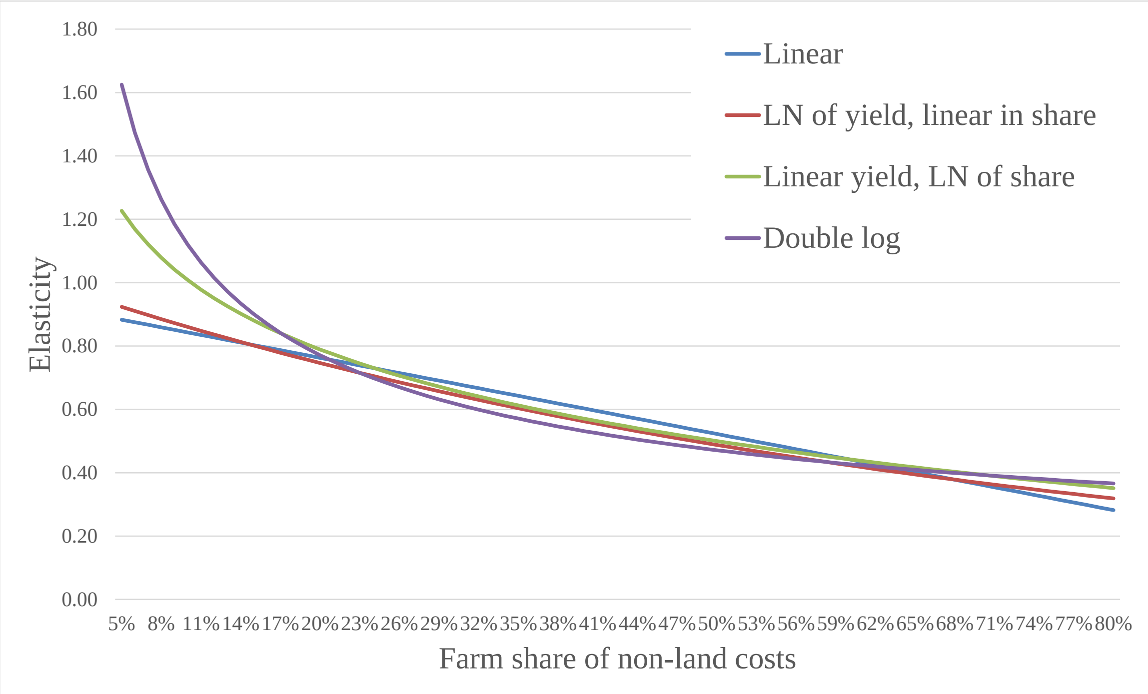
Parameter	***Low value***	***High value***
Input index weight		
Land	0.25	0.50
Farm-owned	0.10	0.50
Input supply elasticities		
Land	0.00	0.00
Farm-owned	0.50	1.00
Purchased	2.50	5.00
Factor substitution		
Land-farm	0.30	0.60
Land-purchased	0.50	1.00
Farm-purchased	0.80	1.60

Note: additional variables, such as purchased cost share and own-price factor elasticities, are calculated as functions of other variables using restrictions implied by data or from theory.

We use a version of the Policy Evaluation Model (PEM) to provide input data that would drive this relationship. We use farm-owned input prices as the proxy for non-traded and non-land input prices in this exercise. This work focuses on factor supply elasticities, cost shares and input demand elasticities to derive the yield response for various levels of non-traded share of non-land costs. To broaden the number of relevant observations, we do not depend on a single set of starting parameters. Instead, we vary them over ranges of values, as defined in the table below. One exception is land supply elasticity which, because of the purpose of the exercise, is always zero.

We draw 500 random observations of these parameters and calculate the yield response as a function of the farm-owned factor share of non-land costs using the formula drawn from the literature. We test various functional forms to relate the two and, as shown in the graph, we find that the differences only become substantial at the extreme, out-of-sample values.

Figure 1. Yield long-run response as a function of cost share



A double-logarithm specification is used for the same two reasons as before, namely consistency with other Aglink-Cosimo equations and to ensure non-negative results.

3.2.4 Timing and moving averages

One key question is the timing of these relationships. While we do not have the data to explore any alternatives using statistical methods and the literature does not provide any clear indication, implementing these model changes requires specifying a time frame. The link from GDPPC to non-traded share of the non-land input price index has a five-year average. For most baseline work, a shorter lag would be simple and might be sufficient, in all likelihood, but a long moving average of GDPPC seems better to stabilize the non-traded weight.

A 10-year moving average in output price relative to input price indices drives long-run yield response. This is admittedly arbitrary: the process might be slower or faster.

The long delay also can raise challenges for baseline development if historical values of all relevant variables are not available.

3.2.5 Testing

Any model change must be tested through repeated use. While this project envisions a scenario experiment, there will likely be at least some revisions as a consequence of future use. That said, the model revisions are intended to have a certain longevity. The changes below are not linked to any base values and could be applied directly to future versions of Aglink-Cosimo with no or little adjustment.

4 Selected long-run elasticities

4.1 Values of long-run elasticities

Calculated long-run yield elasticities for selected crop-country combinations are summarized here. These output are based on the Aglink-Cosimo model and data produced in the context of the 2016 outlook exercise. The relationships given above are introduced into this setting, with some adjustments to handle omissions of historical data that would otherwise interfere with the long lags required to represent delayed price impacts and also accepting the mismatch of the non-traded (NT) price weight in the model as compared to the labour share in non-land input prices used in our theoretical development.

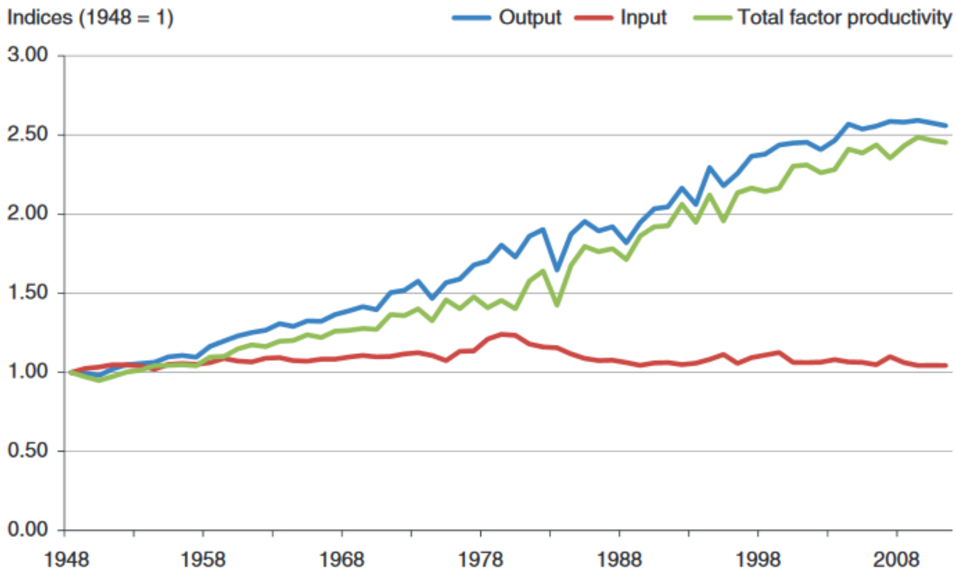
4.2 Putting long-run elasticities in perspective

The short-run, immediate effects of prices represented by the existing Aglink-Cosimo parameters are typically no more than 0.2 and are often 0, with no yield effect. This inelastic response reflects the understanding that there is little to do between planting and harvest to increase yield in most places, no matter how much the prices change in this interval. Moreover, the yield response if prices do happen to be high for a year are often expected to be modest, as well, because prices might not be expected to remain high and there remains only limited scope for adaptation. In those cases price response on national or regional yields might be elastic due as much to compositional changes as anything else (Hertel, Stiegert, and Vroomen, 1996).

The results presented here suggest much stronger long-run response than short-run response. The results are based on findings in the relevant literature, as noted earlier. The intuition is clear: allowing time for all responses to prices, including among input suppliers, leads to larger effects based on the estimated non-traded (labour) input price weight in total input price index, excluding land. Given a decade of higher output prices and consequently an impression of enduring higher returns, input suppliers and farmers would respond, developing and adopting seeds, machinery, and techniques that improve crop yields. Likewise, sustained changes in input prices that endure for decades and decades will eventually cause yield responses. For example, a halving of prices of seeds or machinery could over a long period of time cause large yield response in an economically well-developed sector because seed, machinery, and other input suppliers and farmers would adjust to the new reality.

In considering these results, long-run patterns should be considered, not year-to-year adjustments. Long-run trends in the United States, for example, suggest that all increase in agricultural output from 1948 to 2013 was attributable to productivity increases whereas agricultural inputs remained nearly constant during this period (see Figure 2).

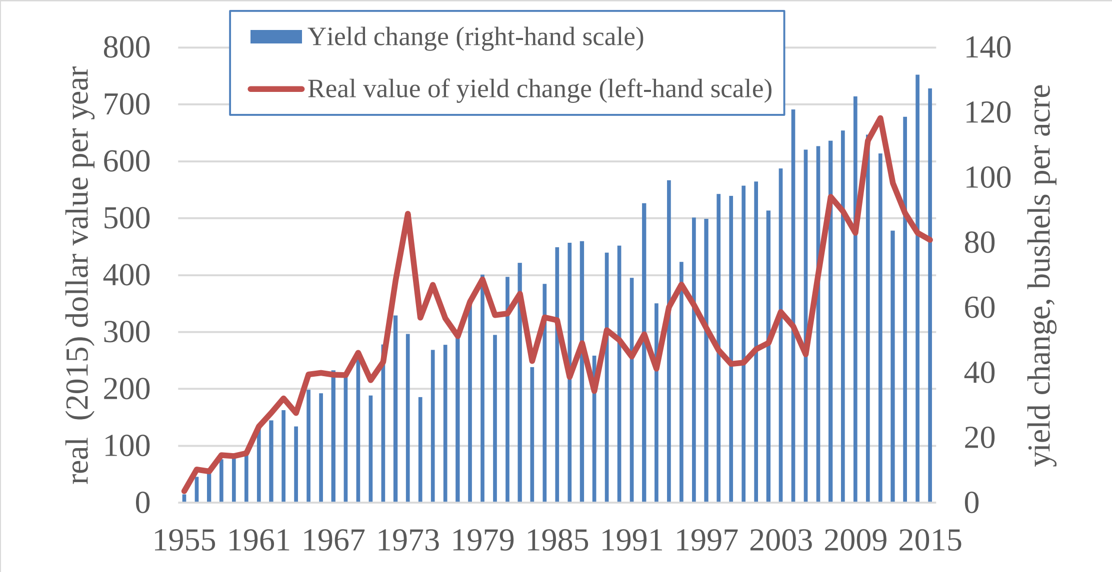
Figure 2. U.S. agricultural inputs, outputs, and productivity, 1948-2002



Source: Copied from ERS (2015).

The implications of productivity for corn yield growth in the United States suggests the creation of a great deal of value. For example, taking the 1950-54 yields as a base, the increase in yield has caused about a hundred more bushels per acre (see Figure 3). This change can be multiplied by the real annual corn farm price to put a value on this trend. Annual real (2015) value of the higher yield rises to hundreds of dollars per acre. In present value terms, this change implies a per-acre value of over 40,000 dollars assuming a 3% discount and twice that amount if discounted at 5%. Of course, this yield could be explained entirely by increasing inputs and corresponding costs, leading to now increase in real returns. However, although input data cannot be reliably attributed to individual commodities, the sector productivity and inputs shown above indicate that inputs cannot explain the majority of this increase in output. This value of rising corn yield was created by people making decisions based on their perceived profits and costs, including farmers and input suppliers, not some underlying trend independent of all economic incentives.

Figure 3. United States corn yield growth since 1950-54, by volume and real value



Sources: crop yield data before calculations for this chart are from NASS; nominal corn price data are from ERS Feed Grain Yearbook tables; and the deflator is a PPI with data from St. Louis Federal Reserve FRED database.

Schultz warns, "The advance in knowledge and useful new factors based on such knowledge are all too frequently put aside as if they were not produced means of production but instead simply happened to occur over time. This view is as a rule implicit in the notion of technological change" (1964). Consistent with this view, the results presented here argue strongly against any long-run assessment of the sector treating as exogenous the long-run improved productivity trends.

Long-run analysis should not have fixed factors, by definition, and productivity should be endogenous over time. While we do not propose to explain how all diverse factors, omitting broad considerations such as patent law and details like the numbers of doctoral degrees in related fields awarded, the results here show that productivity should be viewed as a function of price to at least some extent, or even to a large extent.

A contrarian view, namely that long-run yields are much closer to short-run yields, argues that input suppliers and farmers do not adjust, even if given decades to do so. A view that short- and long-run responses are similarly inelastic suggests that people have very minimal scope to respond to price signals over time. This view would have long-run productivity driven by some external factor that has nothing to do with prices of outputs and inputs in the agricultural sectors.

Arguments that research and development spending motivates the productivity increase must go farther to address the role of price in driving research and development spending over time. Private sector research into corn yields seems likely to be driven primarily by the profit motive and, thus, output and input prices. Public sector research can also be seen to depend partly on price signals, as well, for several reasons. First, to some extent, private sector funding or co-funding for research projects undertaken in academic institutions or government research labs can still play a role. Second, adoption of productivity enhancing measures generated by public or non-profit labs is more likely if prices coax people to do so. Third, public funding for agricultural research and development relating to productivity might very well depend on agricultural market conditions, with greater funding more likely when there is a perception of price-related stress.

The parameters that we provide should take into account all advancements in productivity of land that are generated by farmers, businesses and entrepreneurs, machinery manufacturers and tinkerers, scientists working in private or public venues, and all others who can affect yield to long-lasting changes in relative prices. As such, the parameters include innovations induced by these price signals (Ruttan and Hayami, 1971). The long-run responses reflect the potential that inputs can be substituted and new varieties of inputs can be provided, given time and incentives for agents to adjust, invent, and adopt. Where short-run yield elasticities in the model reflect the annual frequency and represent only the very limited actions that can be taken in the space of a year, or even a growing season, the long-run yield elasticities include all the price responses that are possible from all possible contributors who are placed among a wide variety of locations.

Table 4. Long-run yield elasticities estimated using AGLINK-COSIMO data and relationships outlined above

Maize		Rice		Soybeans		Wheat	
AFL	0.71	AFL	0.70	AFL	0.69	AFL	0.80
AFN	0.66	AFN	0.61	AFN	0.65	AFN	0.91
AFS	0.75	AFS	0.71	AFN	0.65	AFS	0.78
ARG	1.55	ARG	0.82	AFS	0.75	ARG	2.63
ASA	0.75	ASA	0.81	ARG	1.86	ASA	0.82
ASD	0.95	ASD	2.00	ASA	0.82	ASD	1.41
ASL	0.66	ASL	0.75	ASA	0.73	ASL	1.32
AUS	0.80	AUS	0.78	ASD	0.79	AUS	0.93
BGD	0.92	BGD	0.86	ASD	1.53	BGD	0.86
BRA	1.42	BRA	1.34	ASL	0.68	BRA	1.66
CHL	0.76	CHL	0.73	ASL	0.65	CHL	0.76
CHN	1.40	CHN	0.92	BGD	0.73	CHN	1.23
DZA	0.66	DZA	0.61	BRA	1.36	DZA	0.91
E15	1.02	E15	0.73	CHL	1.05	E15	0.98
EGY	0.72	EGY	0.70	CHL	0.75	E15	1.21
ETH	0.75	ETH	0.62	CHN	0.97	EGY	0.83
EUE	0.96	EUE	1.20	CHN	0.90	ETH	0.66
EUW	0.96	EUW	1.20	DZA	0.65	EUE	1.35
GHA	0.87	GHA	0.79	E15	1.21	EUW	1.35
HTI	0.72	HTI	0.75	E15	1.08	GHA	0.94
IDN	0.74	IDN	0.79	EGY	0.72	HTI	0.62
IND	0.80	IND	0.63	EGY	0.71	IDN	0.61
IRN	1.18	IRN	0.72	ETH	0.92	IND	1.58
ISR	0.77	ISR	0.73	EUE	0.98	IRN	0.82

(table continues on the next page)

Maize		Rice		Soybeans		Wheat	
JPN	0.73	JPN	0.76	EUE	1.13	ISR	0.80
KAZ	0.95	KAZ	2.00	EUW	0.98	JPN	0.92
MEX	0.73	KOR	0.70	EUW	1.13	KAZ	1.41
MLE	0.88	MEX	0.70	GHA	0.66	MEX	0.74
MOZ	0.64	MLE	0.79	HTI	0.64	MLE	0.91
MYS	0.70	MOZ	0.69	IDN	0.75	MOZ	0.61
NGA	0.97	MYS	0.70	IND	0.80	MYS	0.61
NMS	1.44	NGA	0.83	IRN	0.80	NGA	2.49
NZL	0.73	NMS	0.73	IRN	1.09	NMS	0.98
OCE	0.72	OCE	0.75	ISR	0.78	NMS	1.49
OCL	0.72	OCL	0.75	ISR	0.76	NZL	0.74
PAK	0.79	PAK	0.83	JPN	1.06	OCE	0.62
PER	0.75	PER	0.66	JPN	0.80	OCL	0.62
PHL	0.72	PHL	0.75	KAZ	0.79	PAK	0.92
PRY	0.65	PRY	0.64	KAZ	1.53	PER	0.76
RUS	1.36	RUS	1.23	KOR	0.69	PHL	0.62
SAC	0.71	SAC	0.66	MLE	0.90	PRY	0.69
SAU	0.84	SAU	1.01	MOZ	0.61	RUS	1.23
SDN	0.75	SDN	0.62	MYS	0.69	SAC	0.89
THA	0.86	THA	0.73	NGA	0.71	SAU	1.15
TUR	0.76	TUR	0.68	NMS	1.49	SDN	0.66
TZA	0.80	TZA	1.07	NMS	1.20	THA	0.74
UKR	0.98	UKR	0.85	OCE	0.64	TUR	0.86
URY	1.08	URY	0.99	OCL	0.64	TZA	0.86
USA	1.82	USA	1.37	PAK	0.74	UKR	1.29
VNM	0.84	VNM	0.86	PER	0.68	URY	1.44

(table continues on the next page)

Maize		Rice		Soybeans		Wheat	
ZAF	0.90	ZAF	0.85	PHL	0.64	USA	1.18
ZMB	0.68	ZMB	0.62	PRY	0.65	VNM	0.61
				RUS	1.40	ZAF	0.96
				RUS	1.30	ZMB	0.69
				SAC	0.76		
				SAU	0.97		
				SDN	0.92		
				THA	0.95		
				TUR	0.73		
				TUR	0.74		
				TZA	0.72		
				UKR	1.26		
				UKR	0.89		
				URY	1.24		
				USA	1.13		
				USA	1.13		
				VNM	0.74		
				ZAF	0.89		
				ZMB	0.80		

5 Scenario analysis

5.1 Definition of experiment

The new model equations are tested as follows.

The labour-related price effects are estimated by changing the input price associated with non-traded goods (GDP deflator term). This shock is applied to all crop input price indices in the model.

Only this term is changed; in no other instance is the GDP deflator altered. In the model, GDP deflator is widely used as a proxy for other prices or sets of prices. However, the experiment in the present case introduces a new dummy or shift variable that only affects the GDP deflator where it is associated with NT input price index weight.

The experiment is conducted twice for two different contexts. In one, currently projected economic development over the near-term future is used. This context is consistent with the usual, ten-year Aglink-Cosimo baseline period. In the second context, the crop production sector is assumed to have been reshaped by a period of economic growth. In this second case, the indicator variable in the yield response equations for country development is set at a higher level to reflect a potential future more than a decade away. The increase in this indicator by 30% corresponds to the level of GDP per person at the end of a 10-year period with 2.6% growth. Thus, this alternative case is not set far into the future, but might instead represent how large the yield elasticity changes would be at the end of the baseline period relative to the start of the period.

In each case, the price of labour is increased by 20% in all years of the simulation. Results compare three-year averages of key variables. The three years are the final three of the ten-year period, to allow time for adjustments.

That said, adjustment is limited. First, price adjustments overall are constrained. While prices of individual countries are permitted to adjust somewhat based on local conditions, global prices are held exogenous in these experiments. This choice is consistent with the objective, namely to highlight global supply response.

A second constraint on adjustment is that long-run yield response is not complete even ten years after a shock. In the representation used here, a ten-year period should span most of the yield adjustment, but still not all. There would be further yield response yet remaining even at the end of the period.

Summary tables below show data from three countries and three crops, only. The three country-crop combinations span a broad range of economic development but are only a manageable subset of the full list of countries and commodities.

5.2 Experiment results

The increase in labour input price to crop production, only, shifts back crop supply. Higher labour price will cause producers to allocate less area and grow less per hectare at any given output price.

The results for the current case show the expected negative impacts on yield and production (see Table 5). Maize, soybean, and wheat yields are lower in the United States, India, and Nigeria. Production impacts are also negative. Technically, production impacts are driven by changes in input prices, which are higher with higher labour price, and also lower gross revenue per hectare as yields contract.

Table 5. Market effects of labour price shock, current

	United States	India	Nigeria
Maize			
Yield	-2.33%	-1.33%	-1.18%
Production	-2.42%	-1.74%	-1.40%
Price	0.53%	5.77%	6.91%
Soybean			
Yield	-2.06%	-1.34%	-1.21%
Production	-3.40%	-1.77%	-1.64%
Price	0.32%	5.50%	7.31%
Wheat			
Yield	-1.83%	-0.96%	-2.21%
Production	-2.71%	-0.51%	-2.44%
Price	0.40%	4.33%	0.05%

Price effects are not zero, even though world prices are not changing. Prices of individual countries can and do change as domestic conditions warrant, to the extent that the domestic price is not integrated into global markets. For the US, unchanging world prices of these crops means that domestic prices change very little, even as domestic supplies contract. Although the model would normally give a more complicated result as world prices change, the changing US production mostly just means less trade in this experiment.

Prices in India and Nigeria change noticeably. The domestic markets are not as well integrated with world markets as in the US case, whether by policy design or due to natural barriers. As a consequence, domestic prices in these two countries rise as domestic production contracts. The exact rate of increase depends on the size of the supply shock, domestic demand elasticities, and the degree to which trade can adjust, if at all, to the price changes. The relative impacts of yield and production signal how area changes. In most instances, production decreases by more than yield, suggesting that less land is planted to a crop. In a few cases, the production decreases by less than the yield, indicating that the relative impacts cause area to shift towards a crop, in net, as its net returns decrease by less than competing crop net returns.

World crop price response, if permitted, would be positive. The reduced crop production in these and all other areas would cause prices to rise. The results for each country-commodity pair would be complicated by the original shocks discussed above, but also by greater output price responses. Relative output and input price effects and competition for area would drive some of the production impacts.

The second scenario sets the same shock in a different context, in a world where there has been greater economic growth. Given the usual patterns of how the share of labour in the input price index evolves with economic development, the implication of greater economic growth is a lower share of labour in crop production and greater yield responsiveness to prices, as discussed earlier. The degree of economic development entertained in this scenario approximately corresponds to the circumstances at the end of a decade of 2.6% growth in GDP per person.

The same labour price shock as before generates similar effects as before (see Table 6). The directional impacts and orders of magnitude are all similar. As before, the effects would be more complicated, but the results already suggest the scale of negative supply impact and the area reallocation.

Table 6. Market effects of labour price shock, more developed agriculture sector

	United States	India	Nigeria
Maize			
Yield	-2.34%	-1.33%	-1.18%
Production	-2.41%	-1.72%	-1.39%
Price	0.53%	5.72%	6.88%
Soybean			
Yield	-2.06%	-1.33%	-1.21%
Production	-3.39%	-1.76%	-1.62%
Price	0.32%	5.46%	7.24%
Wheat			
Yield	-1.84%	-0.95%	-2.21%
Production	-2.71%	-0.50%	-2.44%
Price	0.40%	4.32%	0.05%

Greater economic development has the offsetting yield impacts of (a) lower share of labour and (b) greater yield response to prices. The net effect seen here is that rising labour price has less of an effect on yields after a period of economic development, holding world prices constant. For crops in India and Nigeria, the context of a more developed agriculture influences results, but the similarity of price changes suggests that impacts within the 10-year projection are not very sensitive to this degree of economic development.

The global supply of crops is shifted down by a global increase in labour price to crop producers (See Table 7). The 20% increase in one input has a smaller than proportional impact on input prices overall, as measured by the input price index, and the exact increase varies by country-crop combination. The results using current data suggest that total global grain production falls by about 2%, and global oilseed supplies are almost 5% lower than before taking into account price effects. These changes suggest the size of the supply curve shift if labour prices rise globally.

Table 7. Global crop yield, area, and production response to labour price

	Current	Near-term future
Coarse grains		
Yield	-1.7%	-1.7%
Area	-0.3%	-0.3%
Production	-2.1%	-2.0%
Oilseeds		
Yield	-1.9%	-1.9%
Area	-3.1%	-3.1%
Production	-4.9%	-4.9%
Rice		
Yield	-1.5%	-1.5%
Area	-0.4%	-0.4%
Production	-1.9%	-1.9%
Wheat		
Yield	-1.7%	-1.7%
Area	-0.4%	-0.4%
Production	-2.1%	-2.1%

The yield effects in the context of a more developed world, reflecting the lower share of labour, as well as rising yield responsiveness, are moderated somewhat. The primary reason is the rising weight of other inputs in the input price index relative to labour as countries develop. The 20% labour price increase has a smaller effect on total input prices in the near future after agriculture has reduced labour input further in more places. On the other hand, as yield responsiveness rises with economic development, the world agricultural supply is more sensitive to input prices overall. The net effect shown here is that higher labour prices in the near-future have a decreasing impact on world crop supplies, at least for the values explored in this exercise.

The assumption of 30% greater development, as measured by GDP per person, does not constitute a substantial change along the overall scale of development observed in actual cross-section data. For example, 2016 data suggest that real GDP per capita in several countries averages below USD 1,000 as compared to per capita GDP that averages USD 30-45,000 in Canada, EU, Japan, and the United States. There is a forty-fold difference from USD 1,000 to USD 40,000, so an increase of 30% does little to bridge this gap. A sustained, decade-long growth of 2.6% in per capita GDP corresponds to about 30% greater development. GDP per person would double after a decade of 7.2% growth, but historical evidence suggests that such a pace is unusual.

One conclusion from this exercise might be that the effect of development on labour share and consequently on yield elasticities in the course of a 10-year baseline projection period might be sufficiently modest to be ignored. So while the overall long-run yield response is relevant and can be added to improve accuracy, the potential for further changes in long-run yield response from that starting point can probably be safely ignored in the context of a short baseline period. However, if projections are extended many decades into the future, then the scope for economic development to cause additional yield response to price changes probably can be included to increase accuracy.

6 Conclusions

The results shown here prove that the revised model achieves the intended goals and the outcome is also appealing because implementing these changes to future versions of the model can be conducted at modest cost. The main results of this exercise may be summarised as follows:

- Yield responsiveness to long-run and lasting incentives is represented in a manner that is consistent with lessons learned from the literature.
- The changing role of labour over extended periods of time is represented in a manner that is consistent with lessons learned from the literature.
- The new model functions and effects are linked to an exogenous assumption, that only affects these variables and yet is derived from other, existing macroeconomic assumptions.
- The new model equations can be implemented without a large body of additional data.
- Model code has been developed to introduce these changes into any version of Aglink-Cosimo that is similar to the base model in terms of crop input price indices and yields.
- Long-run yields are calculated based on the relationships drawn from material available in the literature, and existing model data.
- The revised model is tested to show that these changes result in a new model that can and does solve, and generates results that are consistent with the intentions of this exercise.

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Annexes

Annex 1. Model variables and equations

Troll commands to implement the model changes is inserted below. We only present the commands relative to the three crops used in the scenario analysis. Moreover, we limit ourselves only to show selected United States equations as examples.

1. New variables

```
ADDSYM 'N

C.USA_MA_YLD.USA_MA_PPLR      USA_MA_PPCILR
C.USA_SB_YLD.USA_SB_PPLR      USA_SB_PPCILR
C.USA_WT_YLD.USA_WT_PPLR      USA_WT_PPCILR
```

2. New parameters

```
ADDSYM 'P

C.USA_MA_CPCI..SHNT.GDPPC C.USA_MA_PPLR.NT
C.USA_SB_CPCI..SHNT.GDPPC C.USA_SB_PPLR.NT
C.USA_WT_CPCI..SHNT.GDPPC C.USA_WT_PPLR.NT

ADDSYM 'C

C.USA_MA_PPLR.CON   C.USA_MA_CPCI..SHNT.CON
C.USA_SB_PPLR.CON   C.USA_SB_CPCI..SHNT.CON
C.USA_WT_PPLR.CON   C.USA_WT_CPCI..SHNT.CON
```

3. Changed variables and parameters

```
CHANGESYM 'N

USA_MA_CPCI..SHNT
USA_SB_CPCI..SHNT
USA_WT_CPCI..SHNT
```

4. Assign values to new parameters

```
do C.USA_MA_CPCI..SHNT.GDPPC = -0.085303753 ; do C.USA_MA_PPLR.CON = -0.49615859 ; do C.USA_MA_PPLR.NT = -1.099939188 ;

do C.USA_SB_CPCI..SHNT.GDPPC = -0.085303753 ; do C.USA_SB_PPLR.CON = -0.49615859 ; do C.USA_SB_PPLR.NT = -1.099939188 ;

do C.USA_WT_CPCI..SHNT.GDPPC = -0.085303753 ; do C.USA_WT_PPLR.CON = -0.49615859 ; do C.USA_WT_PPLR.NT = -1.099939188 ;

do C.USA_MA_CPCI..SHTR.NT = -0.25 ; do C.USA_MA_CPCI..SHSD.NT = -0.25 ; do C.USA_MA_CPCI..SHEN.NT = -0.25 ; do
C.USA_MA_CPCI..SHFT.NT = -0.25 ;

do C.USA_SB_CPCI..SHTR.NT = -0.25 ; do C.USA_SB_CPCI..SHSD.NT = -0.25 ; do C.USA_SB_CPCI..SHEN.NT = -0.25 ; do
C.USA_SB_CPCI..SHFT.NT = -0.25 ;

do C.USA_WT_CPCI..SHTR.NT = -0.25 ; do C.USA_WT_CPCI..SHSD.NT = -0.25 ; do C.USA_WT_CPCI..SHEN.NT = -0.25 ; do
C.USA_WT_CPCI..SHFT.NT = -0.25 ;
```

5. Calculated intermediate variables

```
ADDEQ bottom

        USA_MA_PPCILR: USA_MA_PPCILR = ((USA_MA_PP(-2)+USA_MA_EPY(-2))/USA_MA_CPCI(-2)+(USA_MA_PP(-3)+USA_MA_EPY(-
3))/USA_MA_CPCI(-3)+(USA_MA_PP(-4)+USA_MA_EPY(-4))/USA_MA_CPCI(-4)+(USA_MA_PP(-5)+USA_MA_EPY(-5))/USA_MA_CPCI(-
5)+(USA_MA_PP(-6)+USA_MA_EPY(-6))/USA_MA_CPCI(-6)+(USA_MA_PP(-7)+USA_MA_EPY(-7))/USA_MA_CPCI(-7)+(USA_MA_PP(-8)+USA_MA_EPY(-
8))/USA_MA_CPCI(-8)+(USA_MA_PP(-9)+USA_MA_EPY(-9))/USA_MA_CPCI(-9)+(USA_MA_PP(-10)+USA_MA_EPY(-10))/USA_MA_CPCI(-
10)+(USA_MA_PP(-11)+USA_MA_EPY(-11))/USA_MA_CPCI(-11))/10   ,

        USA_SB_PPCILR: USA_SB_PPCILR = ((USA_SB_PP(-2)+USA_SB_EPY(-2))/USA_SB_CPCI(-2)+(USA_SB_PP(-3)+USA_SB_EPY(-
3))/USA_SB_CPCI(-3)+(USA_SB_PP(-4)+USA_SB_EPY(-4))/USA_SB_CPCI(-4)+(USA_SB_PP(-5)+USA_SB_EPY(-5))/USA_SB_CPCI(-
5)+(USA_SB_PP(-6)+USA_SB_EPY(-6))/USA_SB_CPCI(-6)+(USA_SB_PP(-7)+USA_SB_EPY(-7))/USA_SB_CPCI(-7)+(USA_SB_PP(-8)+USA_SB_EPY(-
8))/USA_SB_CPCI(-8)+(USA_SB_PP(-9)+USA_SB_EPY(-9))/USA_SB_CPCI(-9)+(USA_SB_PP(-10)+USA_SB_EPY(-10))/USA_SB_CPCI(-
10)+(USA_SB_PP(-11)+USA_SB_EPY(-11))/USA_SB_CPCI(-11))/10   ,

        USA_WT_PPCILR: USA_WT_PPCILR = ((USA_WT_PP(-2)+USA_WT_EPY(-2))/USA_WT_CPCI(-2)+(USA_WT_PP(-3)+USA_WT_EPY(-
3))/USA_WT_CPCI(-3)+(USA_WT_PP(-4)+USA_WT_EPY(-4))/USA_WT_CPCI(-4)+(USA_WT_PP(-5)+USA_WT_EPY(-5))/USA_WT_CPCI(-
5)+(USA_WT_PP(-6)+USA_WT_EPY(-6))/USA_WT_CPCI(-6)+(USA_WT_PP(-7)+USA_WT_EPY(-7))/USA_WT_CPCI(-7)+(USA_WT_PP(-8)+USA_WT_EPY(-
8))/USA_WT_CPCI(-8)+(USA_WT_PP(-9)+USA_WT_EPY(-9))/USA_WT_CPCI(-9)+(USA_WT_PP(-10)+USA_WT_EPY(-10))/USA_WT_CPCI(-
10)+(USA_WT_PP(-11)+USA_WT_EPY(-11))/USA_WT_CPCI(-11))/10   ,
```

6. Estimate share of non-traded (labour) input in non-land input price indices

```
ADDEQ bottom

USA_MA_CPCI..SHNT  : LOG(USA_MA_CPCI..SHNT)  =       C.USA_MA_CPCI..SHNT.CON + C.USA_MA_CPCI..SHNT.GDPPC * LOG
((USA_ME_GDPPC+USA_ME_GDPPC(-1)+USA_ME_GDPPC(-2)+USA_ME_GDPPC(-3)+USA_ME_GDPPC(-4))  /4 ),

USA_SB_CPCI..SHNT  : LOG(USA_SB_CPCI..SHNT)  =       C.USA_SB_CPCI..SHNT.CON + C.USA_SB_CPCI..SHNT.GDPPC * LOG
((USA_ME_GDPPC+USA_ME_GDPPC(-1)+USA_ME_GDPPC(-2)+USA_ME_GDPPC(-3)+USA_ME_GDPPC(-4))  /4 ),

USA_WT_CPCI..SHNT  : LOG(USA_WT_CPCI..SHNT)  =       C.USA_WT_CPCI..SHNT.CON + C.USA_WT_CPCI..SHNT.GDPPC * LOG
((USA_ME_GDPPC+USA_ME_GDPPC(-1)+USA_ME_GDPPC(-2)+USA_ME_GDPPC(-3)+USA_ME_GDPPC(-4))  /4 ),
```

7. Calculate other input price index weights

```
ADDEQ bottom

USA_MA_CPCI..SHTR   :        USA_MA_CPCI..SHTR  =  USA_MA_CPCI..SHTR (-1) +  C.USA_MA_CPCI..SHTR.NT * (USA_MA_CPCI..SHNT -
USA_MA_CPCI..SHNT(-1))   ,

USA_SB_CPCI..SHTR   :        USA_SB_CPCI..SHTR  =  USA_SB_CPCI..SHTR (-1) +  C.USA_SB_CPCI..SHTR.NT * (USA_SB_CPCI..SHNT -
USA_SB_CPCI..SHNT(-1))   ,

USA_WT_CPCI..SHTR   :        USA_WT_CPCI..SHTR  =  USA_WT_CPCI..SHTR (-1) +  C.USA_WT_CPCI..SHTR.NT * (USA_WT_CPCI..SHNT -
USA_WT_CPCI..SHNT(-1))   ,


USA_MA_CPCI..SHSD   :        USA_MA_CPCI..SHSD  =  USA_MA_CPCI..SHSD(-1)  +  C.USA_MA_CPCI..SHSD.NT * (USA_MA_CPCI..SHNT -
USA_MA_CPCI..SHNT(-1))   ,

USA_SB_CPCI..SHSD   :        USA_SB_CPCI..SHSD  =  USA_SB_CPCI..SHSD(-1)  +  C.USA_SB_CPCI..SHSD.NT * (USA_SB_CPCI..SHNT -
USA_SB_CPCI..SHNT(-1))   ,

USA_WT_CPCI..SHSD   :        USA_WT_CPCI..SHSD  =  USA_WT_CPCI..SHSD(-1)  +  C.USA_WT_CPCI..SHSD.NT * (USA_WT_CPCI..SHNT -
USA_WT_CPCI..SHNT(-1))   ,


USA_MA_CPCI..SHEN   :        USA_MA_CPCI..SHEN  =  USA_MA_CPCI..SHEN(-1) +  C.USA_MA_CPCI..SHEN.NT * (USA_MA_CPCI..SHNT -
USA_MA_CPCI..SHNT(-1))   ,

USA_SB_CPCI..SHEN   :        USA_SB_CPCI..SHEN  =  USA_SB_CPCI..SHEN(-1) +  C.USA_SB_CPCI..SHEN.NT * (USA_SB_CPCI..SHNT -
USA_SB_CPCI..SHNT(-1))   ,

USA_WT_CPCI..SHEN   :        USA_WT_CPCI..SHEN  =  USA_WT_CPCI..SHEN(-1) +  C.USA_WT_CPCI..SHEN.NT * (USA_WT_CPCI..SHNT -
USA_WT_CPCI..SHNT(-1))   ,
```

```
USA_MA_CPCI..SHFT   :         USA_MA_CPCI..SHFT  =  USA_MA_CPCI..SHFT(-1)  +  C.USA_MA_CPCI..SHFT.NT * (USA_MA_CPCI..SHNT -
USA_MA_CPCI..SHNT(-1))    ,

USA_SB_CPCI..SHFT   :         USA_SB_CPCI..SHFT  =  USA_SB_CPCI..SHFT(-1)  +  C.USA_SB_CPCI..SHFT.NT * (USA_SB_CPCI..SHNT -
USA_SB_CPCI..SHNT(-1))    ,

USA_WT_CPCI..SHFT   :         USA_WT_CPCI..SHFT  =  USA_WT_CPCI..SHFT(-1)  +  C.USA_WT_CPCI..SHFT.NT * (USA_WT_CPCI..SHNT -
USA_WT_CPCI..SHNT(-1))    ,
```

8. Estimate long-run yield response

```
ADDEQ bottom

          C.USA_MA_YLD.USA_MA_PPLR      :         LOG(C.USA_MA_YLD.USA_MA_PPLR)=    C.USA_MA_PPLR.CON +   C.USA_MA_PPLR.NT  *
LOG ( (USA_MA_CPCI..SHNT(-1) + USA_MA_CPCI..SHNT(-2)+USA_MA_CPCI..SHNT(-3) )/3 )    ,

          C.USA_SB_YLD.USA_SB_PPLR      :         LOG(C.USA_SB_YLD.USA_SB_PPLR)=    C.USA_SB_PPLR.CON +   C.USA_SB_PPLR.NT  *
LOG ( (USA_SB_CPCI..SHNT(-1) + USA_SB_CPCI..SHNT(-2)+USA_SB_CPCI..SHNT(-3) )/3 )    ,

          C.USA_WT_YLD.USA_WT_PPLR      :         LOG(C.USA_WT_YLD.USA_WT_PPLR)=    C.USA_WT_PPLR.CON +   C.USA_WT_PPLR.NT  *
LOG ( (USA_WT_CPCI..SHNT(-1) + USA_WT_CPCI..SHNT(-2)+USA_WT_CPCI..SHNT(-3) )/3 )    ,
```

9. Adjust existing yield equations to add long-run yield response

```
REPEQ     USA_MA_YLD          USA_MA_YLD   :    LOG(USA_MA_YLD) = C.USA_MA_YLD.CON+C.USA_MA_YLD.USA_MA_PP*LOG((USA_MA_PP(-
          1)+USA_MA_EPY)/(C.USA_MA_CPCI.LAG*USA_MA_CPCI(-1)+(1-
          C.USA_MA_CPCI.LAG)*USA_MA_CPCI))+C.USA_MA_YLD.TRND*TRND+LOG(R.USA_MA_YLD)   + MAX(0,C.USA_MA_YLD.USA_MA_PPLR-
          C.USA_MA_YLD.USA_MA_PP)*LOG(USA_MA_PPCILR)  ,

REPEQ     USA_SB_YLD          USA_SB_YLD   :    LOG(USA_SB_YLD) = C.USA_SB_YLD.CON+C.USA_SB_YLD.USA_SB_PP*LOG((USA_SB_PP(-
          1)+USA_SB_EPY)/(C.USA_SB_CPCI.LAG*USA_SB_CPCI(-1)+(1-
          C.USA_SB_CPCI.LAG)*USA_SB_CPCI))+C.USA_SB_YLD.TRND*TRND+LOG(R.USA_SB_YLD)   + MAX(0,C.USA_SB_YLD.USA_SB_PPLR-
          C.USA_SB_YLD.USA_SB_PP)*LOG(USA_SB_PPCILR)  ,

REPEQ     USA_WT_YLD          USA_WT_YLD   :    LOG(USA_WT_YLD) = C.USA_WT_YLD.CON+C.USA_WT_YLD.USA_WT_PP*LOG((USA_WT_PP(-
          1)+USA_WT_EPY)/(C.USA_WT_CPCI.LAG*USA_WT_CPCI(-1)+(1-
          C.USA_WT_CPCI.LAG)*USA_WT_CPCI))+C.USA_WT_YLD.TRND*TRND+LOG(R.USA_WT_YLD)   + MAX(0,C.USA_WT_YLD.USA_WT_PPLR-
          C.USA_WT_YLD.USA_WT_PP)*LOG(USA_WT_PPCILR)  ,
```

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