THE ECONOMIC AND PERFORMANCE IMPACT OF TECHNOLOGY ADOPTION

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DEDICATION

I would like to dedicate this thesis to my wife Eunyoung and my beautiful little girls, Phoebe and Olivia. Your endless sacrifices and tolerance made possible that I reach this objective. No words or actions are sufficient to thank you for all that you have done for me.

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THE ECONOMIC AND PERFORMANCE IMPACT OF TECHNOLOGY ADOPTION

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ABSTRACT

Since first commercialized in 1996, biotech corn has experienced rapid adoption. By 2010 over 75% of the corn planted area in the United States, Canada, Argentina, Brazil, South Africa, and the Philippines was planted with biotech seed. These countries represent a significant presence in the global corn markets—averaging 53% of world production and 83% of world exports from 1996-2010. The purpose of this research is to evaluate the ex post global economic efficiencies generated from the commercialization of biotech corn in these six countries. This study only focuses on the quantifiable market benefits accruing to producers and consumer stakeholders. As such, this analysis does not include the benefits to the input market or the value of non-pecuniary benefits. Global economic efficiency is evaluated on: 1) the extent to which the adoption of biotech corn has impacted yields, and 2) the extent to which the adoption of biotech corn has impacted world production, price and distributional welfare. The extent to which biotech adoption has impacted corn yields is econometrically estimated via a model for technical inefficiency effects in a stochastic frontier production function for panel data. A partial equilibrium seven-region world model of the corn market calibrated to the 2000-2010 decade is developed to evaluate the ex post counterfactual world supply, demand and price impacts of biotech corn adoption. The cumulative 1996-2010 net global economic welfare gain realized from corn biotech adoption was $38.85 billion. Of this total, the largest share ($25.05 billion) went to U.S. corn consumers followed by U.S. producers ($7.13 billion). The cumulative economic welfare gained by all consumers was estimated at $77.97 billion. The adoption of biotech corn has significantly increased production efficiencies of adopting producers which has led to larger and cheaper food supplies for all consumers.

CHAPTER 1. INTRODUCTION

Recent advancements in molecular and cellular technology have led to revolutionary new forms of agricultural inputs. The molecular practice of genomic engineering is now allowing scientists to select a naturally occurring desirable phenotypic trait from one biological organism and asexually introduce it into an entirely different biological organism thus altering the recipients genomic coding such that it then expresses the specifically desirable phenotypic characteristic of the former biological organism. This practice conventionally known as biotechnology has transformed both traditional plant breeding processes through marker assessed methods and on-farm pest management practices through the introduction of herbicide tolerant (HT) and insect resistant (IR) crop varieties. Since first commercialized in 1996 these first generation Genetically Modified (GM) technologies have experienced significant growth.

> "In 2010, the 15th year of commercialization, the global area of biotech crops continued to climb at a sustained rate of 10% or 14 million hectares (notably, the second highest increase in the last 15 years) reaching 148 million hectares. The accumulated hectareage during the first fifteen years, 1996 to 2010, reached, for the first time, more than 1 billion hectares (1.097 billion hectares). Biotech crops have set a precedent in that the biotech area has grown impressively every single year for the past 15 years, since commercialization first began in 1996 with a remarkable ~87 – fold increase since 1996. The number of farmers growing biotech crops in 2010 increased by 1.4 million reaching 15.4 million (up from 14 million in 2009) of which over 90% or 14.4 million were mainly small and resource-poor farmers from developing countries." –C. James [1]

Now after more than 15 years of biotech crop commercialization, an abundance of micro/farm-level studies have been conducted across many regions of the world, and there is beginning to be a general consensus that adoption of this technology has in fact positively impacted yield levels. The principal biotech crops—corn, cotton, and soybeans—claim 30%, 65% and 80% of the global production area respectively, causing policy makers and interest groups to question the intrinsic value of this new technology. Genetically modified (GM) crops have been documented to: 1) increase crop productivity and reduce production costs, thereby contributing to global food, feed, and fiber security, 2) lead to more affordable food, 3) reduce the environmental footprint of agriculture by contributing to more efficient use of external inputs and conserving bio-diversity, 4) mitigate climate change by reducing greenhouse gases, 5) expedite the development of well adapted germplasm for rapidly changing climate conditions, 6) increase stability of production by improving the protection over biotic and abiotic stresses, 7) lower health risks to producer and consumers, and 8) improve economic efficiencies and social benefits [2-4].

Despite the significant amount of positive evidence regarding GM crops, challenges remain regarding the regulation of this technology. From the beginning, the biotechnology revolution in agriculture has been controversial, which has been well documented by both Moschini [5-7] and Pardey [8]. Notably, consumer groups and the general public at large, especially in Europe, have rejected the introduction of GM food into the food system. Widespread reservation about the safety of GM food and about the environmental impacts of GM crops have led to a complex system of pre- and post market obstacles for current and future GM innovations [7, 9]. Such obstacles call for a deeper economic analysis of some regulatory-related consequences of GM crop adoption as noted by Sobolevsky, Moschini, and Lapan [10].

First-generation GM technology has proven safe and effective; it has been enthusiastically adopted by farmers in some developed and developing countries, and it is likely to have lasting effects on agriculture [4]. Nevertheless, a full realization of biotechnology's promises for the agrifood system requires a commitment to Research and Development (R&D).

A distinctive feature of biotechnology innovations is that they are produced mostly from R&D efforts undertaken by the private sector, and they are typically protected by intellectual property rights as defined by Moschini, Lapan, and Sobolevsky [5]. Intellectual Property Rights (IPR) are crucial for private R&D investments in fields (such as biotechnology) in which innovations are easily copied. Research on the relationship between governance and agricultural production efficiencies indicate that to enhance agricultural efficiency, a government must provide an environment where property rights are secure and the gains from investments and efforts are well protected [11]. Lio and Hu [11] insisted that government should refrain from arbitrary actions and unpredictable policies, which may make private interests hesitant to undertake long-term investments [11]. Falck-Zepeda, Traxler, and Nelson [12] stated that the laws and enforcement of intellectual property rights for biological innovations have been strengthened over the past two decades so that protection is now similar to that afforded to other sectors. IPR laws provide investors with limited monopoly power, increasing their ability to appropriate the surplus created by their research effort. This strengthened incentive has spurred private investment in the seed sector, such that twice as many plant breeders are now employed in the private sector as in the public sector [13-14].

In 2012, there were approximately 868 million people suffering from hunger and malnutrition [15]. Global population reached over 7 billion in 2012 and is expected to reach approximately 9.2 billion by 2050 [16]. Population and income growth in developing countries are expected to sustain a strong global demand for increased agricultural output. The challenge of meeting this increasing demand for food, feed, and fiber is magnified by the expansion of biofuel production. Research and investment in technological innovations will be needed to ensure that basic food needs are met in an efficient fashion. While no single innovation is expected to address all the issues, biotechnology can make a vital contribution to the global production systems' goal to provide food, fiber, and feed security.

This research hypothesizes that countries with policies that welcome the contributions of biotechnology and promote the adoption of better and safer products as measured by the national levels of biotech adoption increase producer and consumer welfare.
More specifically this research hypothesizes that the commercial approval and adoption of GM corn has:

1. Increased production efficiencies and the welfare of adopters
2. Increased global production
3. Made food more affordable and increased consumers welfare
4. Increased global economic surplus

This research contributes to the published literature on agricultural biotechnology the first complete ex post characterization of the cumulative welfare effect of biotech corn adoption. The intellectual merit of this dissertation lies in its success in addressing 1) the lack of studies on the distributional impacts of biotech corn adoption, 2) uncertainties regarding elasticity assumptions, 3) distinctions between short- and long-term supply and demand responses, 4) measurement issues regarding aggregate yield and cost impacts, and 5) the lack of empirical research on the temporal impacts of biotechnology adoption. To successfully address these issues this research contributes to literature on the welfare effect of biotech corn by providing:

1. The first global econometric damage abatement supply response measure
2. The first multi-national ex post market assessment of biotech corn
3. The first distributional analysis of the welfare impacts of biotech corn, including
    a. Producer and consumer impacts
    b. Regional impacts
4. The first study to temporally assess the long-run distributional welfare effect of biotech corn adoption.
5. The first sensitivity analysis of the biotech induced market impacts to the assumed supply and demand elasticities.

This research will demonstrate that in regulatory environments that support the commercialization of biotech corn, the extensive adoption of first generation GM crops in large agricultural producing regions has resulted in significant productivity gains as well as welfare gains for both producers and consumers, which are attributable to GM innovations. Improving our empirical understanding of the economic and performance impacts of adoption in the corn market enables decision makers to prioritize the benefits of technology adoption relative to other measurable objective within the decision-making processes. Empirical information related to productivity gains from biotechnology may help improve the efficiency in which other measurable objective are realized.

Evaluating the economic value of efficiency-enhancing innovations is typically done by estimating the associated changes in producer and consumer surpluses in a partial equilibrium setting [17]. This research offers an evaluation of the ex post global economic efficiencies generated from the commercialization of biotech corn in six countries. Global economic efficiencies are evaluated on: 1) the extent to which the adoption of biotech corn has impacted yields and 2) the extent to which the adoption of biotech corn has impacted world production, price and distributional welfare. The extent to which biotech adoption has impacted corn yields is econometrically estimated via a model for technical inefficiency effects in a stochastic frontier production function for panel data. A partial equilibrium seven-region world model of the corn market calibrated to the 1996-2010 crop marketing years is developed to evaluate the ex post counterfactual world supply, demand and price impacts of biotech corn adoption. Evidence generated by this evaluation indicates that the cumulative 1996-2010 global economic net welfare gain realized from added biotech area was $38.85 real 2010 billion. Of this total, the largest share ($25.05 real 2010 billion) went to U.S. consumers followed by U.S. producers ($7.13 real 2010 billion). The cumulative economic benefit gained by all consumers was estimated at $77.97 real 2010 billion. The adoption of biotech corn has significantly increased production efficiencies of adopting producers which has led to larger and cheaper food supplies for all consumers. Nevertheless, it should be noted that all empirical findings within this dissertation should be interoperated with some caveats regarding limitations.

The author acknowledges that by no means are the estimates presented in the following research to be viewed as irrefutable. The author recognizes that improvements can be made, and such improvements could lead to alternative results. However, the primary hypothesis of this research supports the world-wide gains in economic efficiency from the commercial approval and adoption of biotech corn based on the author's; (1) predicted technical inefficiency effects within a stochastic frontier production function for panel data which uses data from the 1996-2010 crop marketing years and (2) the ex post counterfactual international supply, demand and price impacts had those technical inefficiencies not been reduced. Restricted specifications, limited data, and their statistical consequences add uncertainty to the estimated results, but overall, the model operates on proven data and methods. The author determined the merit of these contributions as being valid resources, which add to the body of knowledge and provide information not available elsewhere.

This dissertation is divided into four chapters. Chapter 2 develops the technical inefficiency model embedded within a stochastic frontier meta-production function and econometrically estimates the yield impacts from biotech adoption. Chapter 3 develops a seven-region partial-equilibrium model and simulates the ex post counterfactual impact on world supply, demand, and price. Chapter 4 then compiles the estimates from chapters 2 and 3 and calculates the distributional welfare impacts and evaluates their sensitivity to assumed elasticities.

CHAPTER 2. AGGREGATE YIELD IMPACT 1996-2010

Abstract

This chapter analyzes the effects that commercial adoption of genetically modified corn varieties has on aggregate yield and production efficiencies during the first fifteen years of commercial use (1996-2010). Based on spatial and temporal variations in the rates of genetically modified corn adoption across countries, it is shown that commercial use of this technology has significantly reduced national production inefficiencies and increased yields. Aggregate technical impacts are predicted using a damage control framework within a model for technical inefficiency effects in a stochastic frontier production function for panel data. Results suggest that promoting a more widespread diffusion of genetically modified corn could further amplify global resource use efficiency.

2.1 INTRODUCTION

A successful technology in agriculture leads, among other things, to increases in agricultural productivity so that more measured output can be produced with the same amount of inputs or so that the same amount of outputs can be produced with a smaller quantity of measured inputs. Technology's increases in productivity can stem from the development of new and improved outputs or of new, better, or cheaper inputs. In addition, technology can increase productivity through education, i.e., changes in the knowledge that enables producers to choose and combine inputs more effectively [17]. The types of benefits from biotechnology include the following:

- More output (for a given quantity of inputs)
- Cost savings (for a given quantity of output)
- New and better products

- Better organization and quicker response to changing circumstances

Literature has documented that the research, development and adoption of biotechnology has proven to be successful. First generation biotechnologies have proven to reduce crop losses from insect pests, reduced expenditures on damage control inputs like herbicides, pesticides, and fuel, improved worker safety, and provided a greater flexibility in farm management and lower risk of yield variability [4]. The application of modern biotechnology to plant breeding is considered to be more efficient and quicker than conventional breeding techniques in the development of new and more resilient crop varieties as noted by Hock et al. in [18]. The use of biotechnology or molecular breeding improves the ability to bring new and resilient varieties to the market faster. Improving the ability to bring new varieties to the market increases flexibility of production in response to changes in social and environmental circumstances, e.g., changes in policy or climate. Finally, biotechnology has delivered new and better crops as well as fuel for consumers. Bioengineered soybeans are high in oleic acid and low in saturated fatty acids thereby simultaneously improving oxidative stability while augmenting cold flow which maximizes the fuel characteristics for biodiesel production. Bioengineered soybeans also provide a higher nutritional value for food consumption [19-20].

Despite the volume of evidence demonstrating the benefits, literature has also informed us of the need for more information on the aggregate economic performance impacts of biotech adoption. The objective of this chapter is two-fold: first to explore the existing evidence regarding aggregate measures of yield impacts from GM crop production, and second, to econometrically derive yield/supply response measures of biotech corn adoption. The approach used here is to apply a damage abatement model within a model for technical inefficiency effects in a stochastic frontier production function for panel data of national level yields. In the following sections, an econometric assessment shows if and by how much biotechnology has increased corn yields at the national level. The first attempt to econometrically derive the aggregate yield impacts of GM crop adoption conducted by Sexton and Zilberman [21] indicated significant national yield gains have been realized from the adoption of biotech varieties. This research addresses two important questions: 1) Has biotech corn adoption significantly increased corn yield on a national level? 2) Will an econometric damage abatement model structured within an inefficiency model of a stochastic frontier production function support the aggregate yield impacts documented by Sexton and Zilberman in [21]. To answer these two questions, this research employs a damage abatement model within the model to evaluate technical inefficiency effects of a stochastic frontier production function for panel data of national level yields. The benefit of this method is that it allows for heterogeneous treatments of input functions and can rely solely on production data, so that behavioral hypotheses (e.g., profit maximization) are not required and estimation can proceed in the absence of price data.

The empirical strategy of this chapter is motivated by the global pattern of biotech seed adoption and the need to further the understanding of how biotechnology adoption impacts national yield performance across different technological systems and intensification. By 2010, farmers in 29 countries had planted at least one of the four major biotech crops. The variation in GM adoption across countries and across time enables the econometrician to control for confounding factors at the country level by employing panel methods created by [21]. Panel methods control for endogeneity of adoption at the country level e.g., endogeneity of biotech deregulation by relying on quasi-experimental techniques (difference in differences) across regions, time, and continuous measures of adoption to measure the effect of a treatment at a given time. Nevertheless, of biotech effects remains subject to the biases from endogeneity of adoption at the farm level [21].

Conventional production technologies such as hybrid seeds, fertilizer application and other agronomic practices play a significant role in increasing yield potential; however, farm-level literature indicates that biotic and abiotic damage can significantly affect realized production. While the focus of this assessment will be in terms of the impact of biotechnology adoption, the econometric methods used for this analysis are flexible enough to investigate the effects of a broad set of biotic and abiotic factors as well. A stochastic frontier model applied to national panel data offers the generality and flexibility needed to complement an econometric estimation of the aggregate yield impacts of GM corn adoption.

Lichtenberg and Zilberman's 1986 article [22] on the economics of damage control stated: "Damage control inputs do not increase potential output. Instead, their distinctive contribution lies in their ability to increase the share of potential output that producers realize by reducing damage from *natural* and *human* causes." Within the damage abatement context, it seems that there is currently a paucity of literature aimed at understanding how aggregate pest pressure impacts national corn yields. Much of the applied literature on the damage control model has primarily focused on cross-sectional micro-studies of soybeans and cotton where outward generalization can be problematic. In this section, the author presents the same conceptual model that provides the theoretical foundation for all of the previous damage control empirical analyses except within a broader context more applicable to national level policy consideration.

The following framework embraces the concept of moving beyond the micro field level and applies the damage control model to national-level yield data. It also distinguishes between conventional production inputs that directly affect production, like seed, irrigation, and fertilizer, and damage abating inputs that indirectly affect production by reducing inefficiencies caused by pest pressure.

Let yield per acre, y, be the product of frontier output $f(x, a)$ and damage abatement $g(z, N)$. Frontier output is the maximum attainable output, given production inputs x, that would be obtained if there were no biotic or abiotic pressures. It is increasing in direct production inputs, x, and a heterogeneity parameter a, which characterizes unobservable and/or "quasi" time invariant factors. Damage abatement is the share of crops not lost due to damage control inputs. It is increasing at a decreasing rate in use of damage-abating inputs, z, and decreasing in effective pest pressure, n. Effective pest pressure is the product of damage control parameter δ and initial pest pressure N, i.e., $n = \delta N$, where N is a stochastic variable such that when $\delta = 1$ it denotes complete crop failure. Effective aggregate yield per acre under abatement practice and stochastic pest conditions can be expressed as:

$$y = f(x, a)g(z, N) \qquad \textit{Eq. 2.1}$$

where $f(x, a)$ is the potential output function, and $g(z, N)$ is the damage abatement function.

Utilizing microeconomic principles in Sexton and Zilberman's analysis [21] of optimality conditions, within the context of biotechnology adoption, yields several results important for the subsequent empirical analysis. First, the adoption of GM varieties increases damage abatement, which boosts effective yield under typical conditions as noted by Ameden et al. [23]. This is true so long as the adoption of GM varieties does not require farmers to switch to a less efficient technology that would lower potential output. However, an optimizing farmer may choose to adopt GM seed that may be known to possess ill-adapted properties so long as the savings from other inefficiency control expenditures exceeded the revenue loss from foregone yields.

Second, the yield gains from damage abatement technologies such as GM plant varieties increase with increases in pest pressure, N, and the cost of other chemical abatement practices. Increases in pest pressure increases the damage (yield loss). Increases in the cost of chemical inputs, reduces the amount of these inputs used. Lower usage of chemical damage abatement practices increases yield impacts from biotechnology adoption [24]. Third, technology adoption may cause an increase in the use of production inputs like fertilizer, provided the cost of adoption is relatively lower, thus boosting potential output. As damage abatement increases, so too does the value of marginal product from other production inputs, x, holding input prices constant [21]. Therefore, farmers may employ more direct production inputs. The increase in direct production inputs raises potential output, which boosts effective output by more than the reduction in pest damage.

In Sexton and Zilberman's article [21], this was the key assumption behind the interpretation of their results. Upon a closer investigation of the model output, their counterfactual yields seemed to imply that, had it not been for the adoption of biotech, there would not have been any increases or changes in the use of other direct production inputs like fertilizer, germplasm, irrigation, or improved management practices.

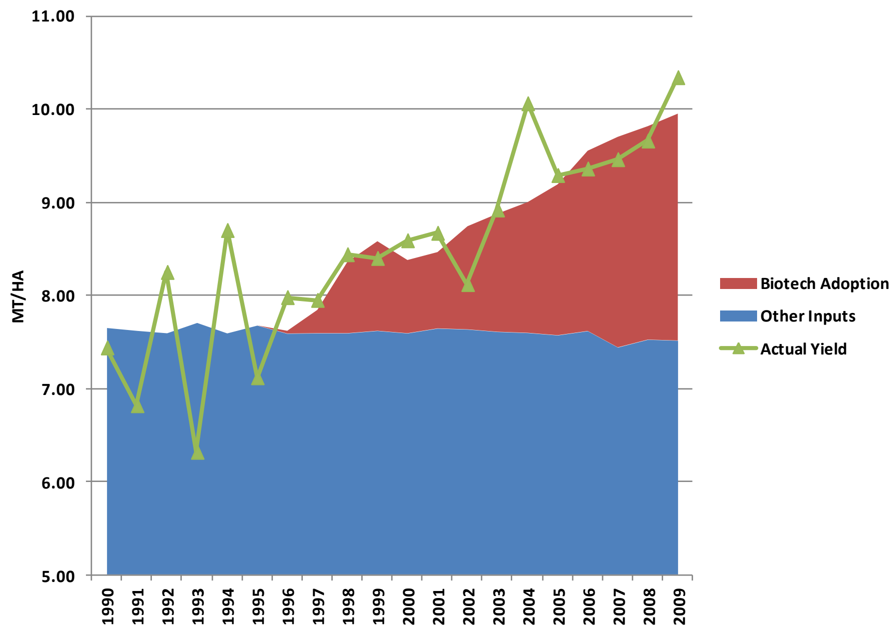

Figure 1. U.S. Yield Growth Model (Sexton and Zilberman, 2010).

Though Sexton and Zilberman [21] were unable to test impacts of GM adoption on input-use in their empirical analysis due to a lack of global data on input-use, they conceptually accounted for it based on the assumption that yield gain associated with "GM crop adoption" exceeds the "gene effect" estimated in much of the previous literature because it captures changes in production inputs as well. Their empirical estimates of the yield gain associated with GM crop adoption had incorporated this additional yield effect as operating through the potential yield function as opposed to the damage abatement function. While this did make their yield estimates unique among estimates of previous analysis and perhaps effectively set the upper bound to the impact of the GM adoption, the size of their documented impacts encourages further investigation into how much the omission of other variable inputs influenced their findings. Finally, the change in yield due to technology adoption is increasing in farm quality, a, and pest pressure, N.

Because a and N cannot be observed, empirical estimates of the yield gain associated with GM crop adoption may be biased. However, according to a 2008 study by Crost [25], panel methods do allow systematic heterogeneity and temporal variations to be controlled via the use of regional and temporal effect variables. Motivated by Coelli, Rao, O'Donnel and Battese [26] and Lichtenberg and Zilberman [22], this dissertation reports that functional properties of the stochastic frontier production function are similar to the functional properties of the damage control production function, and that the stochastic frontier production function proposed by Battese and Coelli [27] can be used to reflect the damage abatement specification. This research broadens the context slightly in order to apply the damage control model to aggregate level data. Specifically the term "damage abatement" will henceforth be used interchangeably with the term "technical efficiency" dependent on the inclusion of non-damage control factors within the damage function. In the following section, this research introduces and applies a stochastic frontier methodology to empirically estimate aggregate yield gains associated with the commercial use of GM corn. Stochastic frontier production analysis preserves the functional form and optimality conditions of the damage abatement specification in that it allows for functional separation between essential production inputs and indirect damage/inefficiency abating inputs. This separation preserves the assumption of diminishing marginal productivity of the pest control provided by the GM traits. The proposed adjustments also allow a broader set of bio-economic factors to be introduced into the specification via the inefficiency function if needed. The stochastic frontier approach adds two fundamentally important components to the analysis – contextual flexibility and the ability to discriminate between random error and firm/national level differences in efficiency. The added contextual flexibility suits the aggregate setting better as it allows other stochastic variables to appear in the damage abatement model. The composite error term aids in its ability to account for the additional statistical noise or measurement error expected from the use of aggregate level data.

The stochastic frontier can be represented by the exact same functional form as the conventional damage abatement specification shown in Equation 2.1. This research defines yield per acre, y, to be the product of potential output $f(x, a)$ and a technical efficiency function $t(z, N)$. Potential output is the output that is obtained if there are no production inefficiencies. It is increasing in production inputs, x, and a heterogeneity parameter a, which characterizes farm quality and is a function of climate and land quality. The technical efficiency function is the share of yield potential not lost due to managerial inefficiencies; thus, by subtracting it from 1 (which assumes the statistical noise = 0) we get the inefficiency function $g(z, N) = [1 - t(z, N)]$. The inefficiency function increases at a decreasing rate in use of inefficiency abating inputs, z, like pest management or human capital, and decreases in effective bio-economic pressure, n. Effective bio-economic pressure, n, is the product of efficient-technology use δ_i and initial bio-economic pressure N, where $\delta_0 = 1$ denotes conventional bio-economic conditions while $\delta_1 < 1$ denotes improved bio-economic conditions i.e. $n = \delta_i N$,. Consequently, for all x and all positive N, $g_1(z, N) \geq g_0(z, N)$, effective yield per acre under bio-economic setting i, then is given by:

$$y_i = f(x, a) g_i(z, N) \qquad \textit{Eq. 2.2}$$

where $g_i(z, N)$ = technical efficiency function

and $f(x, a)$ = potential output function

Furthermore, note that $f(x, a)$ is commonly represented by a Cobb-Douglas functional form and $g_i(z, N)$ possesses the functional properties of a cumulative probability distribution and is defined on the interval of [0,1]. When $g_i(z, N) = 1$, it means that there is complete production efficiency which is representative of a frontier producer and yield losses due to bio-economic related problems that have been minimized by an appropriate level of managerial intensities; when $g_i(z, N) = 0$, it means that the crop was completely destroyed by biotic/abiotic/economic conditions. By definition, Equation 2.2 represents all of the functional characteristics as Equation 2.1 and is thus represented by the same conceptual framework.

The key factor that allows the use of the stochastic frontier model to represent the damage abatement model relies on the stochastic and independent nature of pest pressure on effective yields. The literature on adoption impacts of biotechnology has often relied heavily on deterministic models, though empirical evidence suggests that pest damage and levels of infestation vary between periods. This was especially apparent in studies of the impact of biotechnology in India, where the yield effects from adoption varied considerably due to varying levels of pest infestation as documented by Zilberman, Ameden and Qaim [28]. Thus, the effect of biotech adoption on pest damage is not a single number – it is a statistical distribution, and the specification of adoption is stochastic by nature. By accepting that the initial pest infestation is an independent random variable and that the seed decisions are made before pest infestation levels are known; then using biotechnology adoption within the stochastic component of the stochastic frontier model can be considered as a conventional method of assessing damage abatement [28]. As shown, the damage abatement and the stochastic frontier are econometrically similar enough to be used interchangeably. A stochastic frontier production function preserves the meaningful econometric treatment of conventional inputs and damage control inputs as specified by Lichtenberg and Zilberman [22]. Thus, the stochastic frontier production function is chosen to represent damage abatement technology as the methodological basis for empirical assessment.

2.2 LITERATURE REVIEW

Efficiency, namely, the utilization of resources, is one of the most important topics of economic theory. Kumbhakar and Lovell [29] state that efficiency is the ability of a decision making unit to obtain the maximum output from a set of inputs (output orientation) or to produce an output using the lowest possible amount of inputs (input orientation). This relationship between what a grower produces and what a grower could feasibly produce under the assumption of full utilization of the resources available represents the essence of the stochastic frontier model. By this definition, a technology that increases a grower's or industry's efficiency represents a successful agricultural technology.

A production frontier refers to the maximum output attainable by given sets of inputs and existing production technologies. The production frontier defines technical efficiency in terms of a minimum set of inputs in order to produce a given output or a maximum output produced by a given set of inputs. This approach involves selecting the mix of inputs which produces a given quantity of outputs at a minimum cost, namely the production frontier. If what a producer actually produces is less than what that company or farm could feasibly produce then it will lie below the frontier. The distance by which a producer lies below its production frontier is a measure of the producer's inefficiency [30]. If a producer alters the production practice in such a way that the distance between effective yields realized and the production frontier is narrowed for a given set of technologies, then the producer is said to have lowered his/her production inefficiencies [31].

Farrell [32] was the first to empirically measure productive efficiency in terms of deviations from an ideal frontier. He categorized efficiency into: a) Technical Efficiency (TE), which measures the ability of a firm to obtain the maximum output given inputs, and b) Allocative Efficiency (AE), which measures the ability of a firm to use inputs in optimal proportions given their prices [31]. If only information on input and output quantities is available, then the type of efficiency that can be measured is technical efficiency. Efficiency estimation provides an indication of the percentage by which effective output could be increased in relation to the corresponding production frontier. As indicated by Kokkinou and Geo [31], the reason why estimating efficiency is one of the core tools of economic analysis lies in the need for understanding whether inefficiencies occur randomly or whether some producers or economies have predictably higher levels of inefficiency than others. Bauer [33] indicated that the attraction of the frontier function is attributed to its conceptual consistency with economic theory. Mbelle and Sterner [34] attest that deviations from the estimated frontier can serve as measures of relative efficiency. While the production frontier cannot be directly observed, several techniques have been developed to estimate efficiency. Coelli et al. [26], indicated that frontier and efficiency estimation could be generalized into two classes: a) non-parametric models, utilizing Data Envelopment Analysis (DEA), and b) parametric models, which utilize deterministic or stochastic frontier production functions.

The stochastic frontier production function postulates the existence of technical inefficiencies of production in firms involved in producing a particular output. It is an extension of the deterministic frontier approach in that it accounts not only for technical efficiency, but also for any measurement error or statistical noise. Thus, it allows random events to contribute to the variations in production output. Aigner, Lovell and Schmidt [35] and Meeusen and van den Broeck [36] were the first to independently propose the stochastic frontier production function. Since then there has been a considerable amount of research to extend and apply the model. Reviews of much of this research are provided in Forsund, Lovell and Schmidt [37], Bauer [33], Battese [38], and Greene [39].

The main feature of the stochastic frontier function is the composite error term. The composed nature of the error term allows the presence of factors that might affect the efficiency of the unit in question. A key assumption of the stochastic frontier framework is that firms operate under a given technology to ensure comparability of the technical efficiencies. While this framework has been shown to work well for farm level studies in which the sample of farms are actually utilizing similar production technologies, the same may not be said when a farm or farm aggregates operate under significantly different production technologies [40]. It may be the case that the use of aggregate country level panel data mitigates some of the variation in production technologies by averaging across intraregional technologies. It may also be the case that narrowing in on response functions of a homogeneous commodity like corn in combination with the use of aggregate country level panel data may also mitigate some of the variations in production technologies found in total factor productivity analysis. Nevertheless, production technology differences are still a real and present complication.

Fortunately, a key assumption was made by Hayami and Ruttan [41] indicating that a single production function could actually be utilized to depict technical possibilities available for a specific industry in different countries or regions. However, it was noted that producers do not operate on a universal micro-production function. In short, what Hayami and Ruttan [41] specified as early as 1970 was that the “secular” or “metaproduction” function is the envelope of all countries’ production possibilities, given their resource endowments and technologies. Thus, having interest in generating aggregate measures that are comparable, this research leverages Hayami and Ruttan’s [41] postulate that a single production function could be utilized to depict technical possibilities available for a specific industry in different countries or regions as defensible evidence that a meta-production function suffices as a conventional framework for applied aggregate supply analysis. Since the meta-production function was first proposed in 1970, it has been widely adopted by researchers to study the determinants of inter-farm/sector/country efficiency differences (see Liu and Zhuang [42], Kudaligama and Yanagida [43], and Lio and Hu[11]).

Battese, Rao, and O’Donnell [40] presented a stochastic metafrontier model by which comparable technical efficiencies can be estimated. Their metafrontier function served as an overarching function of a given mathematical form that encompassed the deterministic components of the stochastic frontier production functions for firms that operate under different technologies. Their metafrontier concept was also based on the concept of the metaproduction function defined by Hayami and Ruttan [44]: “The metaproduction function can be regarded as the envelope of the commonly conceived neoclassical production functions.” While their extension significantly corrected for potential differences in production technologies, the use of aggregate level data and the small number of adopting regions limit its use within the following analysis.

2.3 CONCEPTUAL MODEL

Fitting frontier production functions to farm-level data is a well established approach confirmed by Battese [37] in 1992. Stochastic frontiers, of the type originally suggested by Aigner, Lovell and Schmidt [35] in 1977 discriminated between random errors and farm level differences in efficiency. Battese and Coelli [27] introduced the inefficiency model in which the efficiency differences are simultaneously estimated from the stochastic frontier and explained by farm-specific variables. The stochastic frontier production function for panel data is

$$Y_{it} = f(x_{it}\beta)exp(V_{it} - U_{it}) \quad with\ U{\sim}|N(z_{it}, \sigma^2)|\ and\ \ V{\sim}N(0, \sigma_V^2) \quad \textit{Eq. 2.3}$$

where Y_{it} denotes the observed production output at the t-th observation $(t = 1,2, \dots, T)$ for the i-th country $(i = 1,2, \dots, N)$; $f(x_{it})$ is the conditional mean function given inputs x_{it}; x_{it} is the $(1 \times k)$ vector of values of known factor inputs in production and other explanatory variables associated with the i-th country at the t-th observation; β is a $(1 \times k)$ vector of unknown parameters to be estimated; the real valued error components V_{it}'s are assumed to be iid $N(0, \sigma_V^2)$ random errors, independently distributed of the U_{it}s. The U_{it}s are non-negative random variables, associated with technical inefficiency of production, which are assumed to be independently distributed; as such, the production relationship has a multiplicative error process composed of $V_{it} \in \mathbb{R}$ and $U_{it} \in \mathbb{R}_{+}$. Assuming $E[exp(V_{it})|x_{it}] = 1$, the conditional mean of Y_{it} (given x_{it}) is

$$E[Y_{it}|x_{it}] \equiv h(x_{it}) \leq f(x_{it}) \qquad \textit{Eq. 2.4}$$

where the inequality is strict for some x_{it} under technically inefficient production. For example, the relationship between $h(x_{it})$ and $f(x_{it})$ under technically inefficient production is illustrated in Figure 2.2. Under technical efficiency,

$$E[exp(-U_{it})|x_{it}] = 1 \qquad Eq.2.5$$

and the conditional mean achieves the production frontier such that $h(x_{it}) = f(x_{it})$ for all x_{it}.

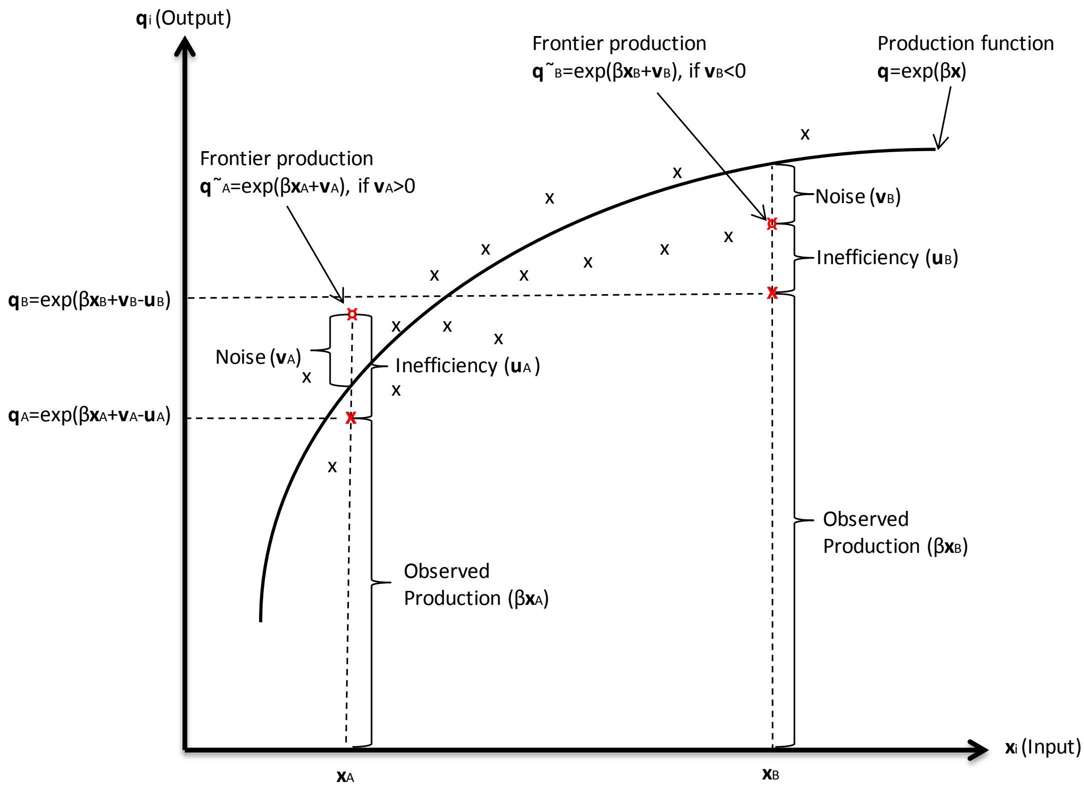

Figure 2. Stochastic Frontier Model.

While $Y_{it} = f(x_{it})exp(V_{it} - U_{it})$ specifies the stochastic frontier production function in terms of the conventional production technologies, the technical inefficiency effects, the U_{it}s, are also assumed to be a function of a set of explanatory variables, z_{it}, and an unknown vector of coefficients, δ. The explanatory variables in the inefficiency model may include some input variables in the stochastic frontier provided the inefficiency effects are stochastic.

Parametric stochastic frontier models have long taken the following forms where the conditional mean $f(x_{it})$ function is typically specified as a Cobb-Douglas or translog production function, and the real valued error component V_{it} is commonly represented as a $N(0, \sigma_v^2)$ random variable, while the model for positive-valued error components U_{it} is often obtained by truncation of the normal distribution with mean, $z_{it}\delta$, and variance, σ_u^2; z_{it} is a $(1 \times m)$ vector of explanatory variables associated with technical inefficiency of production of firms over time; and δ is an $(m \times 1)$ vector of unknown coefficients.

The aggregate damage control or technical inefficiency of an individual country is defined in terms of the ratio of the observed output to the corresponding frontier output, conditional on the levels of inputs used by that country. When the model in Equation (2.2) is assumed, the technical efficiency of production for the i-th firm at the t-th observation is defined by the following equation.

$$TE_{it} = \frac{observed\ output}{potential\ maximum\ output} \qquad Eq.\ 2.6$$

$$= \frac{f(x_{it})exp(V_{it} - U_{it})}{f(x_{it})exp(V_{it})}$$

$$= exp(-U_{it})$$

$$= exp(-z_{it}\delta - W_{it}), 0 \leq TE_{it} \leq 1$$

which will ensure that the observed outputs lie below the frontier. The technical inefficiency effect, U_{it}, in the stochastic frontier model (Equation 2.2) could be specified as,

$$U_{it} = z_{it}\delta + W_{it} \qquad \textit{Eq. 2.7}$$

where the random variable, W_{it}, is defined by the truncation of the normal distribution with zero mean and variance, σ_u^2, such that the point of truncation is $-z_{it}\delta$, i.e., $W_{it} \geq -z_{it}\delta$. Truncating W_{it} from below such that $W_{it} \geq -z_{it}\delta$ satisfies the requirement that $U_{it} \geq 0$ [45]. These assumptions are consistent with U_{it} being a non-negative truncation of the $N(z_{it}\delta, \sigma_u^2)$-distribution. This specification follows from Huang and Liu [46] who consider a stochastic frontier production function in which the non-negative technical inefficiency effects are a linear function of variables involving firm characteristics. The additive random error of the inefficiency model, W_{it}, is assumed to be the truncation of a normal distribution with mode zero, whose point of truncation is dependent on the firm characteristics, such that the inefficiency effects are non-negative. Hence, the random errors are not required to be non-negative, as in the model of Reifschneider and Stevenson [47]. This dependence on firm characteristics means that the W_{it}-random variables are not identically distributed nor are they required to be non-negative. Additionally, the mean, $z_{it}\delta$, of the normal distribution, which is truncated at zero to obtain the distribution of U_{it}, is not required to be positive for each observation [48] [27]. Together these characteristics imply that the mean truncation of the normal distribution is allowed to be different for different firms and time periods, but the variances are assumed to be the same. Thus, technical inefficiency effects are assumed to be independent non-negative truncations of normal distributions with unknown variance, σ_u^2, and means, $z_{it}\delta, i = 1,2, \dots, N$; and $t = 1,2, \dots, T$.

As stated above, following the inclusion of the second random error, the stochastic frontier model asserts that the composite error term of the function is made up of two independent components: 1) a two-sided random term, V_{it}, and 2) a one-sided positive error term U_{it} where random component V_{it} represents factors that cannot be controlled by production units, measurement error, and omitted variables. U_{it} represents the shortfall from the production frontier due to pest damage or other inefficiencies.

To summarize the set of assumptions regarding the random components of the errors term, the stochastic frontier production function asserts the following from Aigner et al. [35]:

1. $v_{it} \sim iidN0, \sigma_v^2$
2. $u_{it} \sim iidN^+(\mu_{it}, \sigma_u^2)$
3. Each v_{it} is distributed independently of each u_{it}
4. Both v_{it} and u_{it} are uncorrelated with explanatory variables in x_{it}
5. $E[v_{it}] = 0$, (zero mean)
6. $E[v_{it}^2] = \sigma_v^2$, (homoskedastic)
7. $E[v_{it}, v_{jt}] = 0$, for all $i \neq j$ (uncorrelated)
8. $E[u_{it}^2] = \sigma_u^2$, (homoskedastic)

9. $E[u_{it}, u_{jt}] = 0$, for all $i \neq j$ (uncorrelated)

Thus, the noise component, v_{it}, is assumed to have properties that are identical to those of the noise component of a conventional linear regression model. The inefficiency component has similar properties except it has a non-zero mean according to Coelli et al. [26].

In the preceding model, the technical inefficiency effects are modeled in terms of various explanatory variables which could include functions of firm and management characteristics and a period of observation. Battese and Coelli [27] state that the general frontier model may include intercept parameters and a period of observation in both the frontier and the model for the inefficiency effects, provided the inefficiency effects are stochastic and not merely a deterministic function of relevant explanatory variables (i.e., $U_{it} = z_{it}\delta$ is not estimable for all choices of z_{it} and x_{it}).

In order to calculate inefficiency model, maximum likelihood estimation is used to take into consideration the asymmetric distribution of the inefficiency term. Greene [49-50] argues that the only distribution which provides a maximum likelihood estimator with all desirable properties is the Gamma distribution. However, following van den Broeck, Koop, Osiewalski, and Steel [51], the truncated distribution function is preferred, which better distinguishes between statistical noise and inefficiency terms according to Mastromarco [45]. Technical efficiency of country *i* at time *t* are represented by

$$TE_{it} = \exp(-u_{it}) = \exp(-\delta z_{it} - w_{it}). \qquad \textit{Eq. 2.8}$$

Jondrow, Knox Lovell, Materov, and Schmidt [52] suggest a measure of efficiency based on the distribution of inefficiency conditional to the composite error term, $u_{it}|\varepsilon_{it}$ (where $\varepsilon_{it} = v_{it} - u_{it}$). The distribution contains all the information that ε_{it} yields about u_{it}. The expected value of the distribution can therefore be used as a point estimate of u_{it}. When the distribution of the inefficiency component is a truncated distribution, a point estimate for technical efficiency TE_{it} is given by

$$E(TE_{it}) = E[\exp(-u_{it})\,|\varepsilon_{it}] = \frac{[\Phi\left(-\sigma_* + \frac{\mu_{it}^*}{\sigma_*}\right)]}{[\Phi\left(\frac{\mu_{it}^*}{\sigma_*}\right)]} \exp\left[-\mu_{it}^* + \frac{1}{2}\sigma_*^2\right] \qquad \textit{Eq. 2.9}$$

with

$$\mu_{it}^* = (\sigma_v^2 z_{it}\delta - \sigma_u^2 \varepsilon_{it})(\sigma_u^2 + \sigma_v^2)^{-1} \qquad \textit{Eq. 2.10}$$

$$\sigma_*^2 = \sigma_u^2 \sigma_v^2 (\sigma_u^2 + \sigma_v^2)^{-1} \qquad \textit{Eq. 2.11}$$

where $\Phi(.)$ represents the standard normal cumulative density function. Implementing this procedure requires estimates of μ_{it}^* and σ_*^2. In other words, we need estimates of the variances of the inefficiency, σ_u^2, and random components, σ_v^2, and of the residuals $\hat{\varepsilon}_{it} = y_{it} - x_{it}\hat{\beta}$ [45]. Then by replacing the unknown parameters in Equations (2.10-2.11) with the maximum likelihood estimates, an operational predictor (Equation 2.9) for the technical efficiency of the country i in the time period t is obtained.

The prediction of the technical inefficiency is based on the conditional expectation, represented by Equation (2.9), where $\varepsilon_{it} = v_{it} - u_{it} = y_{it} - f(\boldsymbol{x}_{it})$ is the combined error term. The first step in predicting the technical efficiency TE_{it}, is to estimate the parameters of the stochastic frontier model. Even though, the entire term $(v_{it} - u_{it})$ is easily estimated for each observation, a major problem is how to separate it into its two components [31]. Estimation and hypothesis testing procedures in the case of the stochastic frontiers is more complicated because the right-hand side of the model includes two random terms – a symmetric error, v_{it}, and a non-negative random variable u_{it}. Trying to solve this problem, the relationship between y_{it} and v_{it} could be expressed as

$$y_{it} \sim iidN(x_{it}\beta, \sigma^2), \qquad \textit{Eq. 2.12}$$

where y_{it}denotes the i^{th} observation on the dependent variable; x_{it} is a vector containing the explanatory variables; β is a vector of unknown parameters. The assumption of an asymmetric inefficiency distribution as well as symmetric normal noise distribution suggests the use of maximum likelihood estimation method [26].

Since, Aigner, Lovell, and Schmidt [35] first estimated the unknown parameters of the stochastic frontier model using the f maximum likelihood method. Maximum likelihood estimation is a popular statistical method used for fitting a mathematical model to real world data as demonstrated by Greene [49] and Coelli [53]. The concept of maximum likelihood estimation is based on the idea that a particular sample of observations is more likely to have been generated from some distributions than from others. Consequently, the maximum likelihood estimate of an unknown parameter is defined by Kokkinou [31] to be the value of the parameter that maximizes the probability (or likelihood) of randomly drawing a particular sample of observations. In order to use the maximum likelihood principle to estimate the parameters of the production frontier function model, this author makes the assumption that the errors are iid normal random variable with zero mean and constant variance, as previously listed by Coelli et al. [26]. Aigner et al. [35] focused on the implicit assumption that the likelihood of inefficient behavior monotonically decreases for increasing levels of inefficiency. They parameterized the log-likelihood function for the half-normal model in terms of the variance parameters:

$$\sigma^2 = \sigma_u^2 + \sigma_v^2 \qquad \textit{Eq. 2.13}$$

where σ^2 is a measure of the total variance of the combined error term, ε_{it},

$$\varepsilon_{it} = v_{it} - u_{it} \qquad \textit{Eq. 2.14}$$

and the asymmetry of the distribution of the error term is the central feature of the model. The degree of asymmetry can be represented by the following parameter:

$$\lambda^2 = \frac{\sigma_v^2}{\sigma_u^2} \geq 0 \qquad \textit{Eq. 2.15}$$

The larger λ is the more pronounced the asymmetry will be. On the other hand if $\lambda = 0$, there are no technical inefficiency effects and all deviations from the frontier are due to noise. This would imply that the symmetric error component dominates the one-sided error component in the determination of ε_{it} [31, 45].

Given the specifications of the above model, the null hypothesis that the technical inefficiency effects are not random is expressed by $H_0\colon \gamma = 0$, where $\gamma = \sigma_u^2(\sigma_u^2 + \sigma_v^2)^{-1}$. Further, the null hypothesis that the technical inefficiency effects are not influenced by the level of the explanatory variables in Equation (2.7) is expressed by

H_0: $\delta' = 0$, where δ' denotes the vector, δ, with the constant term, δ_0, omitted, given that it is included in the expression, $z_{it}\delta$.

Considering that the distribution of the composite error term is asymmetric (because of the asymmetric distribution of the inefficiency term), a maximum likelihood estimator that takes both asymmetric and symmetric aspects of the composite error term into consideration should give more efficient estimates, at least asymptotically according to Mastromarco [45]. Thus because this dissertation focuses on modeling damage/inefficiency abatement, the author has assumed a truncated normal distribution of $u_{it} \sim N^{+}(\mu_{it}, \sigma_u^2)$. Using this parameterization, the log-likelihood function is

$$lnL(y|\alpha, \beta, \lambda, \sigma^2) = -\frac{N}{2} ln\left(\frac{\pi}{2}\right) - Nln\sigma - N\Phi\left(\frac{-\mu}{\lambda\sigma}\right) + \sum_{i=1}^{N} ln\Phi\left(\frac{-\mu\lambda^{-1} - \varepsilon_i\lambda}{\sigma}\right) - \frac{1}{2\sigma^2}\sum_{i=1}^{N} \varepsilon_i^2 \qquad \textit{Eq. 2.16}$$

where the log-likelihood function is expressed in terms of two parameters $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \frac{\sigma_u}{\sigma_v}$ [45].

To estimate the parameters of the production function and the parameters in the equation of the expected inefficiency, this research uses a time-series single-stage model to investigate the damage abatement effects in stochastic production frontiers, applying the Maximum Likelihood method proposed by Kumbhakar [54], Reifschneider and Stevenson [47] and Battese and Coelli [27]. Since Equation (7.16) is highly nonlinear, first-order conditions cannot be solved analytically for α, β, σ^2 and thus λ becomes an iterative optimization procedure applied to maximize the likelihood function. This involves selecting starting values for the unknown parameters (values were selected using OLS) and systematically updating them until the values that maximize the log-likelihood function are found as suggested by Coelli et al. [26].

Due to the stochastic nature of the damage abatement model in which damage abated by biotech adoption is treated as an independent random variable, damage abatement can be measured in the aggregate as increased technical efficiency within the stochastic frontier model. Relating back to the original objective of determining the aggregate yield impacts of GM corn adoption, the predicted change in the technical inefficiency represent the additional production not lost to damage and/or production inefficiencies which are attributable to the adoption of GM corn.

Since the estimated variances of the inefficiency, σ_u^2, and the random noise component, σ_v^2, are assumed constant, the model's composite residuals, ε_{it}, is defined as randomness that is independent of the region i's production input influence in time t. Therefore, the operational predictor for the technical inefficiency, shown in Equation (2.6), can then be used to discover the technical efficiency or damage abatement impacts of biotechnology adoption, z_{it}. The inefficiency model in Equation (2.7) includes an intercept parameter δ_0 which is constant across production units to ensure that the parameter estimates associated with biotechnology adoption are unbiased. Furthermore, the model treats multiple observations of the same unit as being obtained from independent samples making the model a pooled estimator [45, 55].

To derive the counterfactual yield for years 1995-2010, this research utilized each region's unique operational technical efficiency predictor to assess the yield impacts of biotechnology adoption. Impacts are calculated by assuming different biotechnology adoption paths into the maximum likelihood operational predictor and calculating the difference.

$$\Delta Y_{it} = \exp(x_{it}\beta - v_{it})\, E(TE_{it}) - \exp\,(x_{it}\beta - v_{it})E(TE^{*}_{it}) \qquad \textit{Eq. 2.17}$$

where $E(TE^{*}_{it})$ is calculated such that the contributions of biotechnology adoption within the technical inefficiency model, $u_{it} = z_{it}\delta + w_{it}$, where $z = 0\ \forall\ t \in (1995,2010)$.

2.4 DATA AND MODEL SPECIFICATION

This study uses annual country level panel data on corn yield across a set of 10 countries collected from the USDA FAS PS&D for years 1980-2010 [56]. Considering that the objective of this analysis was to provide accurate measures of the yield impacts from biotechnology adoption, this author's methodology attempts to reduce the standard errors of the coefficients. The goal, therefore, was to eliminate a significant share of the technological disparities by restricting the set of countries pooled for estimation to only biotech adopting countries along with three other non-adopting countries who possessed similar production technologies to act as a non-adoption control group. For the estimation aggregate yield function, five agricultural inputs are used, including fertilizer, irrigation, planting densities for open pollinated varieties (OPV) and hybrid varieties (HV) and a technology trend variable. The definitions of these variables are as follows. Fertilizer is measured as the national average nitrogen fertilizer application rate (in kilograms per hectare). Fertilizer data was compiled from the Center for Agriculture and Rural Development (CARD) World Fertilizer Model [57]. National fertilizer application numbers used in the analysis are presented in Table 1.

Table 1. Fertilizer Application KG/HA

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Argentina	35	52	48	44	42	48	55	54	66	81	65	79	79	51	57	69
Canada	132	174	146	133	142	139	135	150	131	144	127	147	149	120	132	168
United States	139	144	142	144	144	147	135	145	144	136	146	175	167	165	169	150
South Africa	56	59	52	59	48	48	59	57	52	60	35	71	55	41	40	36
Brazil	26	37	37	38	38	52	48	47	64	63	51	48	58	58	51	53
Spain	192	250	213	211	206	201	199	169	201	200	153	163	200	147	151	212
Chile	207	306	230	188	227	227	227	202	255	276	172	172	258	281	209	230
France	156	203	168	149	157	150	150	130	142	154	122	125	160	124	116	147
Philippines	39	56	57	42	43	48	56	50	56	58	44	40	39	32	25	25
Poland	96	139	129	98	97	108	102	97	120	120	109	114	147	136	127	141

Irrigation is measured as the national average volume of irrigation water applied per hectare (cubic meters per hectare). Due to the lack of time series data on crop specific irrigation application, this variable is a constant value across the estimation period. National average data on the amount of irrigation water used to produce a ton of corn was gathered from the Water Footprint Network [58].

Evaluating the contribution of crop breeding to increasing yields requires an examination of changes in other cultural practices [59]. Duvick [60], stated that “Yield potential per plant has not increased over the years. Increased yielding ability of newer hybrids is owed primarily to increases in stress tolerance that in turn provide tolerance to higher plant densities. Compared with older hybrids, today’s hybrids produce approximately the same amount of grain per plant but on considerably more plants per unit area.”

An analysis of a long series of corn hybrid trials carried out by Duvick and collaborators from 1972–2000 indicated that in the case of maize, breeding gains were closely associated with higher optimum plant densities which led to increased yield per acre, despite the fact that maximum yield per plant did not significantly increase over the years[60-62]. Based on this observation, the author used Open Pollinated Variety (OPV) and Hybrid Seed Variety, (HV) seed planting densities, measured as their respective share of total seed planted multiplied by the national average planting density for each type of seed, to proxy breeding advances in stress tolerance. Calculating planting densities (both OPV and HV) as a weighted average also helps to control technology/genetic differences between various countries. In this way both technology shifts (shifting from OPV to HV) in the frontier and movement along (increasing planting densities) the frontier can be captured in a fewer number of explanatory variables. Nevertheless, treating genetic improvements in such a dichotomous fashion prevents the models ability to empirically determine how each variety (OPV or HV) has improved over time. For example, in the U.S. where plantings are and have been 100% HV such a specified variable will not contribute any information regarding the annual varietal gains from breeding had it not been from increases in planting densities. National average planting densities of OPV and HV seed was compiled from The Context Network annual international market research survey [63].

Considering that it is also useful to understand the relative importance of introducing GM traits, when compared with the gains associated with conventional hybridization. Duvick [60], indicated that genetic improvements and changes in cultural practice (management) are responsible for all increases in on-farm yield gains. But, because breeding and management interact with each other, neither factor could have raised yields without simultaneous and complementary change in the other. Numerous estimates of genetic gains of maize hybrids have shown, without exception that genetic yield gains during the past 70 years have been positive and linear. For example the results of [60] suggested that, from the 1930s–2001, crop breeding (hybridization) contributed to linear US yield gains at the farm level of 1.8 bu per acre per year. Following from this line of thought, the author estimates country specific linear historical growth rates to control for the omission of country specific technical trends in genetic and cultural patterns. The country specific technical trend is measured as a country specific trend variable scaled respectively to each 1980-1996 annual growth rate in yield. To generate this set of technical trends, a simple OLS regression was run, where yields were regressed against a linear trend variable over the period 1980-1996. From each regression the slope coefficients were collected and used to scale country specific trend variables to capture regionally conditioned growth trends of omitted information such as breeding improvements of cultural/agronomic improvements. The author acknowledged that this result is heavily dependent on a linear extrapolation of pre-biotech historical estimates of an annual yield gain from conventional breeding and cultural change, which may not be appropriate. This methodology does, however, improve the author's ability to estimate a regional and temporally specific "one-off" impact of GM adoption by conditioning in the regional specific pre-biotech trends. But it does not, however, allow the author to estimate the effects of GM technology on the rate of yield improvement over time (as it might be expected that molecular breeding accelerates the selection process).

Finally, for the simultaneous estimation of the technical inefficiency model, only the damage abatement variable, national biotechnology adoption, is selected for estimation. Biotechnology adoption is measured by the share of area planted that was planted to a biotechnology traited seed variety. National biotechnology adoption data was gathered from The International Service for the Acquisition of Agri-biotech Applications (ISAAA) [64] and Brookes [65]. The author notes that the limitation of this measure is that it prevents any inference into the explicit gains associated with any single trait or stacking of traits, unless of course a particular region has only adopted a single trait.

It is important to note that while the selected data are expected to contribute significantly to the explanation of international yields and yield changes, the author does not have complete details about each country's technology. One likely problem with the approach, particularly when aggregate national level data are used, is that underlying heterogeneity in climate and environmental conditions such as soil, rainfall and temperature are largely neglected; thus, potentially important interactions between environmental factors and the genetic potential and production efficiency of a GM cultivar may not be identified [59, 66-68]. Furthermore, other problems may arise, at the national level, from the difficulties in obtaining accurate data on input use by crop which reflects the sum of all farm-level choices when risk and uncertainties are involved, or from the lack of a suitable measure of the effect of management [69-70]. As previously indicated, it is difficult to disentangle these effects from simultaneous changes in breeding and cultural practices (such as biotechnology). Given the uncertainty of the rate at which cultural changes occur and contributes to yield, there is significant potential for selection bias when the impact of newly available technologies is analyzed [71].

Empirical results are obtained by using the stochastic frontier production model with time-varying inefficiency effects modeled as a function of biotechnology adoption. The Cobb-Douglas stochastic frontier production function model, which is assumed to represent the production technology for corn growers in a particular country, is defined by

$$lnY_{it} = \beta_0 + \sum_{m=1}^{5} \beta_m x_{mit} + V_{it} - U_{it}. \qquad \textit{Eq. 2.18}$$

where the U_{it}s are assumed to be defined by

$$U_{it} = \ \delta_0 + \delta_1(z_{it}) + W_{it} \qquad \textit{Eq. 2.19}$$

where:

1. lnY_{it} denotes the natural logarithm of the total quantity of output for the ith country in the tth year (in thousands of metric tons)

2. x_1 denotes the natural logarithm of the national average nitrogen fertilizer application rate (kg/ha)

3. x_2 denotes the natural logarithm of the national average volume of irrigation water used, (m^3/ha)

4. x_3 denotes the natural logarithm of the national weighted average planting density of OPV seed, (kg/ha)

5. x_4 denotes the natural logarithm of the national weighted average planting density of HV seed, (kg/ha)

6. x_5 denotes the country specific technology trend, (mt/ha)

7. z_{it} is a continuous measure of biotechnology adoption, as measured by the share of area planted with biotech seed, (% of area harvested)

8. $\beta_1 = \frac{dlnY_{it}}{dlnx_{1it}}$ is the elasticity of output with respect to nitrogen fertilizer application

9. $\beta_2 = \frac{dlnY_{it}}{dlnx_{2it}}$ is the elasticity of output with respect to irrigation application

10. $\beta_3 = \frac{dlnY_{it}}{dlnx_{3it}}$ is the elasticity of output with respect to saved seed density

11. $\beta_4 = \frac{dlnY_{it}}{dlnx_{4it}}$ is the elasticity of output with respect to hybrid seed density

The V_{it}s are assumed to be independently and identically distributed as $N(0, \sigma_v^2)$ random variables, independent of the U_{it}s. The U_{it}s are assumed to be independently and identically distributed non-negative random variables, obtained by truncation (at zero) of the $N(\mu_{it}, \sigma_u^2)$-distribution; and the β_i's, μ_{it}, σ_V^2 and σ_u^2 are unknown parameters to be estimated by methods of maximum likelihood.

The stochastic frontier model, defined by Equations 2.18 and 2.19, is estimated using data on population averages in a given country. The technical efficiency of the ith country, given the observation for the tth period, relative to its regional frontier, $TE_{it} = \exp\left(-U_{it}\right)$, is predicted as proposed in Battese and Coelli [72].

Table 2. Summary Statistics on Output and Inputs

		Yield	Fertilizer	Irrigation	Open Pollinated Planting Density	Hybrid Planting Density	Biotechnology Adoption
		MT/HA	KG/HA	M^3/HA	KG/HA	KG/HA	%
All	Min	1.5	24.9	0.1	0.1	4.4	0%
All	Mean	6.5	122.9	1063.2	2.9	17.9	19%
All	Max	11.3	305.7	5135.2	15.2	27.9	99%
All	Std Dev	2.9	69.5	1770.7	3.9	6.8	29%
Adopters	Min	2.0	24.9	0.1	0.1	5.4	0%
Non-Adopters	Min	1.5	25.6	0.1	0.2	4.4	0%
Adopters	Mean	6.8	120.9	748.0	2.6	17.7	36%
Non-Adopters	Mean	6.3	125.2	1402.9	3.2	18.1	0%
Adopters	Max	10.3	227.1	3890.4	14.2	27.9	99%
Non-Adopters	Max	11.3	305.7	5135.2	15.2	27.5	0%
Adopters	Std Dev	2.6	64.8	1376.5	3.4	6.0	32%
Non-Adopters	Std Dev	3.2	74.6	2071.2	4.4	7.6	0%

Output and input data are summarized in Table 2, which reports the mean, minimum, maximum, and the standard deviation of the variables used. The variation in the data is sufficient to allow estimation of the production relationships across time.

Of primary interest to this analysis is the derivation of the damage abated through the adoption of biotechnology. After the operational predictor of technical efficiencies has been conditioned by the MLE estimates, this author was able to derive the population average supply shifts of the damage abated from biotechnology inputs. Recent modifications to the FRONTIER 4.1 model now allow estimation of a simultaneous system of equations. Thus, country specific effects, U_{it}, will be modeled simultaneously along with the stochastic frontier production function.

In summary, guided by the functional properties of the stochastic frontier, this research attempts to econometrically identify how adoption levels in each country have contributed to increasing effective yield by reducing inefficiencies or the distance between the effective yield levels and their suggested, technologically defined, frontier yield levels.

2.5 RESULTS

As detailed above, the stochastic frontier analysis examines the relationship between output and input levels, using two error terms – V_{it} and U_{it}. V_{it} represents statistical noise in which the mean is zero and the variance is constant. U_{it} represents technical inefficiency (or in this case damage abatement) and can be expressed as a truncated normal distribution. Technical efficiency is measured by separating the technical inefficiency, U_{it}, component from the overall error term.

The distance between a country's effective average yield and the estimated frontier represents its relative inefficient use of production inputs, random shocks, or measurement error. This author assumes a Cobb-Douglas production frontier function for national corn yields, covering years 1995-2010. The production function, defined for national corn yield, is a function of fertilizer, irrigation, and planting densities. The model allows inefficiency (damage abatement) to vary over time, and the inefficiency effects are a function of the level of biotechnology adoption.

To estimate the parameters of the production function and the parameters in the equation of the expected inefficiency, this research's methodology employs a single-stage panel model as described by Battese and Coelli [27] to investigate the inefficiency/damage effects in the stochastic production frontier, applying the Maximum Likelihood Method. The program, FRONTIER 4.1, was used to produce estimates for these technical efficiencies for all firms in the periods in which they are observed in the panel data. The maximum-likelihood estimates of the parameters in the Cobb-Douglas stochastic frontier production function, given the specifications for the damage abatement effects, defined by Equations 2.18 and 2.19 are given in Table 3.

Table 3. Maximum-Likelihood Parameter Estimates: Stochastic Frontier Production Function for Global Corn Production, (1995-2010)

		MLE Estimates for Model		
Variables	Parameter	Coefficient	Standard Error	T-Stat
Production Frontier				
Constant	β_0	-0.38	0.11	-3.42
Fertilizer	β_1	0.22	0.03	8.33
Irrigation	β_2	0.06	0.01	11.79
OPV Planting Density	β_3	0.10	0.01	7.14
HV Seed Planting Density	β_4	0.50	0.03	15.25
Technology Trend	β_5	0.09	0.01	7.23
Sum of Elasticities		0.97		
Inefficiency Model				
Constant	δ_0	0.33	0.03	11.57
Biotechnology Adoption	δ_1	-0.61	0.12	-4.92
	$\sigma_S^2 \equiv \sigma_V^2 + \sigma_U^2$	0.02	0.00	6.92
	$\gamma \equiv \sigma_U^2/\sigma_S^2$	0.76	0.11	6.86
Log (likelihood function)		111.33		
LR test of the one-sided error		90.28		
Number of cross-sections		10		
Number of time periods		16		
Total number of observations		160		
Mean technical efficiency		0.78		

Source: The estimated standard errors for the parameter estimators are presented below the corresponding estimates. These values are generated by the computer program, FRONTIER 4.1. The nine countries included in this model are: Argentina, Brazil, Canada, United States, Chile, South Africa, Spain, France, Poland, and the Philippines.

As with the last model, the log-linear Cobb-Douglas functional form statistically tested to be the most adequate functional form. There is strong statistical evidence to support that the model represents a frontier function, and that the frontier model, with variables to explain the inefficiencies, is a preferred model. The sum of the elasticities is .97, which is an indication that there may be decreasing returns to scale, since if all the inputs were increased by 1%, output would rise by .97%. The χ^2 test shows that the null hypothesis of constant returns to scale (elasticities sum to unity) cannot be rejected, so the coefficients may be interpreted as factor shares in output. However, such interpretation must assume that there are no omitted variables.

All the elasticities are significantly different from zero and hybrid seed planting density has the largest impact (0.50), followed by fertilizer (0.22), technology trend (0.09), OPV planting density (0.10) and then irrigation (0.06). The elasticity of yield with respect to fertilizer application is 0.22 indicating that a 1% increase in fertilizer application would increase output by 0.22% and the t-statistic shows this estimate is significantly different from zero at the <.001% confidence level. With respect to the inefficiency model the coefficient on biotechnology adoption is negative and statistically significant. This is strong statistical evidence that biotechnology adoption significantly reduces inefficiencies in aggregate corn production.

The γ statistic is used to determine whether this is indeed a frontier model and not simply a mean response function. Here $\gamma = 0.76$, indicating that the function is significantly reflective of a frontier function wherein technical inefficiencies have statistically accounted for a large share of the divergence from the meta-production frontier. This is not surprising since Table 3 shows that the mean level of efficiency for the full sample was 0.78. The adopters had a higher mean efficiency of 0.82 as compared with the mean of 0.72 for those who did not use GM corn. However, considering that several of the adopting countries had 0 to very low adoption levels in many of the earlier years, it is interesting to consider the average efficiency levels at the beginning and end of the estimation period. By replacing the unknown parameters in Equations 2.10-2.11with the maximum likelihood estimates, the operational predictor can be used to obtain the counterfactual technical efficiency of the country i in the time period t. The last two years' mean efficiency for adopters was 0.91 compared to 0.69 for the non-adopters. Table 4 compares the 1995-1996 average technical efficiencies against the 2009-2010 average technical efficiencies for the adopters relative to the non-adopters.

Table 4. Average Technical Efficiency: Adopters and Non-adopters of Biotechnology, %

	1995-1996	2009-2010
Adopters	0.72	0.91
Non-Adopters	0.73	0.69

Note: values are reported as period average technical efficiencies

As presented in Table 4, over the 15 years of biotech corn adoption, adopting regions experienced a 19% increase in the efficiency measured by the effective use of fertilizer, irrigation, seed, and breeding improvements brought into production. In contrast non-adopting regions sharing similar production technologies experienced a 4% decrease in the efficiency with which production inputs were used. Table 5 illustrates the changes in technical efficiencies for each country.

Table 5. Country Level Technical Efficiencies of the Corn Production

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Difference
Argentina	0.72	0.73	0.91	0.84	0.87	0.85	0.90	0.94	0.94	0.97	0.94	0.98	0.92	0.93	0.98	0.94	0.24
Canada	0.87	0.80	0.82	0.93	0.93	0.80	0.84	0.87	0.94	0.94	0.96	0.95	0.95	0.98	0.96	0.98	0.13
United States	0.79	0.85	0.85	0.90	0.90	0.90	0.91	0.87	0.92	0.96	0.93	0.92	0.94	0.94	0.96	0.94	0.13
South Africa	0.72	0.67	0.61	0.61	0.79	0.69	0.73	0.64	0.69	0.79	0.83	0.60	0.90	0.96	0.96	0.96	0.26
Brazil	0.67	0.67	0.68	0.68	0.65	0.73	0.70	0.78	0.72	0.66	0.70	0.77	0.81	0.76	0.86	0.84	0.18
Spain	0.60	0.64	0.69	0.71	0.70	0.68	0.70	0.70	0.66	0.71	0.72	0.71	0.70	0.73	0.90	0.70	0.18
Chile	0.88	0.78	0.82	0.73	0.79	0.77	0.82	0.83	0.79	0.77	0.80	0.79	0.67	0.66	0.70	0.68	-0.13
France	0.74	0.74	0.80	0.77	0.79	0.79	0.75	0.78	0.64	0.76	0.71	0.72	0.74	0.75	0.75	0.70	-0.02
Philippines	0.70	0.66	0.63	0.76	0.74	0.75	0.73	0.75	0.72	0.72	0.79	0.80	0.86	0.85	0.84	0.89	0.19
Poland	0.65	0.61	0.65	0.72	0.71	0.72	0.73	0.74	0.63	0.67	0.68	0.53	0.71	0.65	0.69	0.64	0.03

Note: Difference is calculated as (2009-2010 avg. TE) minus (1995-1996 avg. TE)

Farm-level biotech-induced yield impacts documented within the literature provide the author with a base from which to assess the plausibility of the estimated impacts. A summary of the collected data from an exhaustive review of the literature are presented in Table 6.

Table 6. Summary of Published Farm-Level Corn Yield Impacts

	United States	Canada	EU	Philippines	South Africa
Mean	5.7%	5.6%	8.0%	27.7%	15.3%
Min	2.6%	1.0%	5.2%	13.6%	3.7%
Max	9.1%	10.3%	17.5%	36.9%	30.8%
N	14	4	36	18	19

While the sample size of documented findings may be smaller and considered an imperfect comparison due to fact that most documented findings came from field trial conditions [73] and were conducted almost entirely in the first few years of adoption, the comparison still provides a valuable point of reference. Furthermore, the observed variation in the averages for each country indicate that a significant difference exists between developed and developing countries. Qaim and Zilberman's [24] table of expected yield effects of pest resistant transgenic crops in different regions (Table 8), shows an expected lower yield benefits of biotech crops in developed countries with low to medium pest pressure, and high availability and adoption of chemical alternatives (which is the case for the US and Canada). In contrast, areas such as the Philippines, Argentina, and Brazil where pest pressure is high and the availability and adoption of chemical alternatives remains low, the yield effect was expected to be high. However, it should be noted that the lack of data on expected pest pressures and availability and adoption of chemical alternatives prevents any control for the effects of these factors. The author recognizes this as a limitation and admits that there may exist variable omission bias.

Table 7. Expected Yield Effects of Pest-Resistant Transgenic Crops in Different Regions (Qaim and Zilberman, 2003)

Region	Pest pressure	Availability of chemical alternatives	Adoption of chemical alternatives	Yield effect of transgenic crops
Developed countries	Low to medium	High	High	Low
Latin America (commercial)	Medium	Medium	High	Low to medium
China	Medium	Medium	High	Low to medium
Latin America (non-commercial)	Medium	Low to medium	Low	Medium to high
South and Southeast Asia	High	Low to medium	Low to medium	High
Sub-Saharan Africa	High	Low	Low	High

Source: Qaim and Zilberman (2003)

While there is some data on chemical use there is not data on pest pressure. The most common way in which changes in pesticide use with GM crops have been presented is in terms of the volume (quantity) of pesticide applied. While comparisons of total pesticide volume used in GM and non-GM crop production systems can be a useful indicator of environmental impacts, it is an imperfect measure because it does not account for differences in the specific pest-control programs used in GM and non-GM cropping systems. For example, different specific products used in GM versus conventional crop systems, differences in the rate of pesticides used for efficacy, and differences in the environmental characteristics (mobility, persistence, etc.) are all masked in general comparisons of total pesticide volumes used [65]. Furthermore, there are significant gaps in the availability of herbicide or insecticide usage data in most countries that differentiate between GM and conventional crops. Due to gaps in data and comparability issues, this research does not explicitly control for variations in chemical abatement practices.

Like Sexton and Zilberman [21] the empirical strategy of this chapter was motivated by the global pattern of biotech seed adoption and the need to further the understanding of how biotechnology adoption impacts national yield performance across different technological systems. While Sexton and Zilberman [21] were the first to attempt to econometrically derive the aggregate yield impacts of GM crop adoption, the size of their documented impacts encouraged further investigation into how much the omission of other variable inputs influenced their findings.

In their evaluation, they used analysis of variance to decompose yield per acre to different components. Their analysis applied an approach introduced by Just and Zilberman [74] to decompose variable input among crops. The approach allocates output among crop-types. They assumed that at each time and location the yield per acre of each crop with a given technology is fixed, but these yields per acre vary across crops, technologies, and time. Their approach allowed them to rely on a minimal amount of data to decompose yields.

While their analysis contributed an accurate application of the Just and Zilberman [74] input allocation model to various seed technologies, their empirical estimates of the yield gain associated with GM crop adoption were assumed to have operated through a deterministic potential yield function as opposed to a stochastic damage abatement function. In essence, they estimated the population average effects of the trait or set of traits whose expression does not vary, which implied that there is no diminishing marginal productivity of the pest control provided by the traits. A key assumption used to control for the weaknesses of the specification was that yield gain associated with "GM crop adoption" exceed the "gene effect" estimated in much of the previous literature because it captures changes in production inputs as well (assuming those changes were caused by the adoption of the GM crop).

As illustrated in Figures 3-8 the magnitude of their estimates seemed to imply that, had it not been for the adoption of biotech, there would not have been any improvements or changes in the use of other direct production inputs like fertilizer, germplasm, irrigation, or improved management practices. Though Sexton and Zilberman [21] were unable to test impacts of GM adoption on input-use in their empirical analysis due to a lack of global data on input-use, evidence generated by this author suggests that their omission of other variable inputs and specification has significantly overestimated the impacts of GM crop adoption. Therefore, while this research finds that there is significant statistical evidence to support that GM corn adoption has increased national level corn yield it does not, however, support the levels presented by [21].

Figures 3-8 compares each country's predicted yield impact from the damage abatement model against the estimated impacts of the Sexton and Zilberman model. The author also reports the predicted yield impact from the damage abatement model to show the percentage change as well as improve comparability with other published findings. To generate the estimates for the Sexton and Zilberman [21] model, this author compiled a similar data set and replicated their procedure. Parameter estimates derived from econometric replication matched that which was documented in [21]. Each of the following country level discussions presented next begins with a brief overview of the technologies adopted, levels of adoptions of each technology, and the expected yield impacts. Expected yield impacts are based on average finding from an exhaustive literature review. The yield impacts generated by the stochastic damage abatement model were then checked against a priori expectations to determine the overall plausibility of the predicted results, followed by a comparison against the yield impacts estimated from the econometric panel method found in Sexton and Zilberman's [21] paper.

2.5.1 United States

The US was one of the first countries to adopt biotechnology in 1996. By 2010 86% of the area planted was planted with a biotech traited seed variety. It is important to note that GM traits are generally classified as either Herbicide Tolerant (HT) or Insect Resistant (IR). While the biotech adoption-induced yield-impacts developed in this chapter did not explicitly attribute the yield gains as either HT or IR GM technologies, there are, however, different prior expectations regarding impact between HT and IR traits. HT corn has been used commercially in the US since 1997, and in 2010 was comprised 70% of the total US maize crop; however, the main benefit from HT corn has been to reduce production costs as yield impacts were documented to have only been in the 0-1% range [75].

Within the US, IR corn can be further disaggregated into Corn Borer Resistant (IR-CB) and Root Worm Resistant (IR-WR). The main farm impact from both technologies has been increased average yields. IR-CB corn was first planted in the US in1996, and in 2010, seed containing IR-CB traits was planted on 63% of the total US corn crop. Much of the analysis in early years of adoption indentified an average yield impact of about +5.7%. IR-RW corn has been planted commercially in the US since 2003. In 2010, 53% of the total US crop contained an IR-WR corn trait. The main farm income impact has been higher yields of about 5% relative to conventional corn [65]. While it is generally accepted that the trait for corn borer resistance will not add to yield in periods of low pest pressure [76], there is some evidence that there may be an increase in yield for hybrids with the rootworm resistance trait because of increased drought tolerance [4], and that herbicide-tolerant traits are not yield-neutral [77-78]. Probably the most comprehensive study on the contributions of GM corn to changes in US corn yields was conducted by Nolan and Santos [75]. Utilizing 163,941 independently-run experimental field trials of corn hybrids, submitted by corn breeders to the agricultural extension services of various universities, their findings indicated that the effect of stacking traits leads to gains in yield (as expected) but that the pathways for such gains are not necessarily linearly additive. Estimated impact of IR and HT stacks ranged from 6-7%.

Furthermore, Hutchison et al. [79] examined impacts over the 1996-2009 periods and considered the positive yield impact on non GM IR crops due to the 'area-wide' adoption of IR technology as increased adoption of IR seed reduces overall presence of insects. Integrating key findings of his work could lead to an average yield impact at 9%.

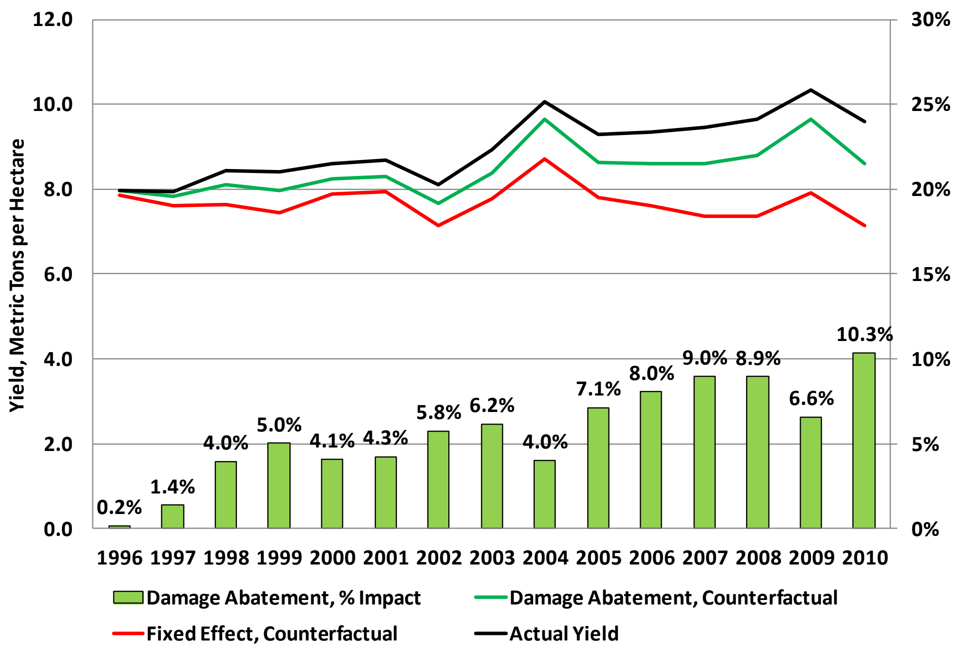

Figure 3. Estimated United States Yield Impacts (Metric Tons per Hectare).

Considering that by 2010 over 86% of US planted area contained GM technology the predicted yield impacts presented in Figure 3 matches a-priori expectation. Results presented in Figure 3 indicate three additional patterns which support the plausibility of predicated impacts. First, the aggregate impacts in the early years, particularly in 1998 and 1999, are slightly higher than expected given the lower national levels of adoption. However, the choice of crop variety is an endogenous variable which might lead to bias from self-selection. A common occurrence within the farm-level impact studies is that it is expected that the most efficient farmers adopt GM crops at a higher rate than their less efficient peers [71]; therefore, assuming that was the case, it is plausible that the national yield impact from 1999 adoption levels was 4% (National adoption was 31% in 1999). Second, the model predicted significant reductions in the yield impacts for years 2004 and 2009. In 2004 and 2009 above average growing conditions led to record setting US yield levels. Above average weather condition is a stochastic event which is outside of the growers control. Remember that Technical Efficiencies (TE) are random variables and are predicted from a distribution of inefficiency conditional to the composite error term which is made up of symmetric and asymmetrical components. Unexpected events affect model's ability to capture the contribution of biotech adoption especially when stochastic environmental events simultaneously increase efficiency. In 2004 and 2009 the frontier production landed above the estimated deterministic production function which implied a positive error, $V_{it} > 0$. Since technical efficiencies are measured as the difference between the deterministic frontier and the observed output, the inefficiency effect was undermined by the positive stochastically improved state of nature. Thus, a majority of the composite error for US yield in those years was predicted to have come from large positive unexplained random events limiting the ability to predict the biotech impact. The author discovered that the smaller 2006 and 2009 yield impacts were within a priori expectation because IR corn is considered to be a risk-decreasing technology [4]. Technologies that generate smaller impacts in good states of nature are considered to be risk-decreasing [25, 80]. Therefore, these finding support the hypothesis that GM corn technology possesses an additional 'insurance' function beyond the pesticide reduction/yield increasing attributes in most analyses.

The benefit from the technology would then include a positive risk premium obtained in addition to benefits (expected value of profits) obtained from mean output increases [25, 80]. Finally, the third observation that supports the plausibility of the predicted national aggregate yield impacts stems from rapid increases in the impact from 2005-2008. The significant increases in the annual impacts across these years also coincide with prior expectations as significant increases in GM stacked cultivars and the introduction of IR-RW occurred over the same period. Nevertheless, total biotech corn adoption was the only explanatory variable within the damage abatement model; therefore, the model did not explicitly differentiate the impact between traits and/or trait packages. While the prediction of this effect may have been coincidental, the models maximum likelihood estimates conditioned from regional and temporal specific errors was within a priori expectations.

While the estimates generated from the damage abatement model did support the hypothesis that the adoption of GM corn has significantly increased aggregate US yield, the inclusion of additional information and the damage abatement functional form caused this research to conclude that impacts generated by [21] are significantly overestimated.

2.5.2 Canada

Like the US, Canada was an early adopter of biotechnology, which now dominates Canada’s production of corn. In Canada, HT corn was first planted commercially in 1999. In 2009, the proportion of total plantings accounted for by varieties containing a HT trait was 53%. As in the US, the main benefit has been to reduce costs and to improve profitability levels[65]. IR-CB corn has also been grown commercially in Canada since 1996. In 2010 it accounted for 78% of the total Canadian corn crop of 1.2 million ha. IR-RW cultivars were planted commercially in Canada for the first time in 2004. In 2010, the area planted to IR-RW varieties was 23%. The impact of GM IR varieties (CB or RW) in Canada have largely been assumed to have yield and cost of production impacts very similar to the US [65]. However, Baute, Sears, and Schaafsma [81] published estimated yield impacts of IR-CB between 4.3-5.6% relative to conventional yields. Ma, Meloche, and Wei [76] assessed the agronomic and yield performance of transgenic rootworm trait and indicated that over the 2003-2005 production years, grain yields of the Bt hybrid were 11–66% greater than the *untreated* non-Bt isoline hybrid.

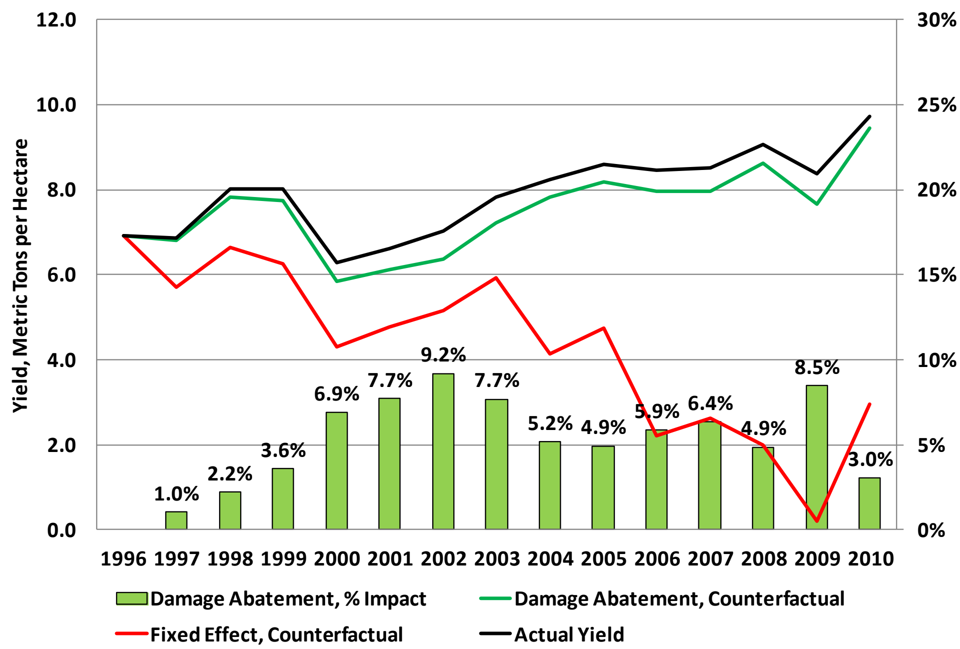

Figure 4. Estimated Canadian Yield Impacts (Metric Tons per Hectare).

Corn is grown primarily in the eastern provinces of Ontario and Quebec. Despite differences in adoption rates, predicted impacts support the a priori expectation that impacts in Canada are largely similar to that realized by the US. Given Canada's significantly smaller amount of area in corn production relative to the US, the adoption of GM corn reached much higher levels in a shorter amount of time. This resulted in significantly larger national yield impacts in earlier years as compared to the US. By 2001 almost 50% of Canada's corn designated areas were planted with a GM cultivar. Adoption levels backed off significantly in 2004 resulting in an observed reduction in yield impacts. As indicated in the US results, IR corn varieties are considered as risk-decreasing. As a result, above average growing condition years 2005, 2008, and 2010 resulted in smaller relative yield impacts. As presented in Figure 8 the 2006-2010 average national yield impacts ranged between 4.9-8.6% which put them within range of other published findings.

As with the US yield impacts, the estimates generated from the damage abatement model did support the hypothesis that the adoption of GM corn has significantly increased aggregate Canadian yield. However, based on this research the author concludes that impacts generated by [21] are significantly overestimated. The counterfactual estimate generated by [21] illustrates the problems associated with a variable omission, not treating biotechnology as a damage abatement input, and population average fixed effect approaches to estimating the impacts of biotechnology adoption.

2.5.3 Argentina

IR varieties were commercially available earlier than HT varieties. IR varieties were first planted in 1998. In 2010, IR corn traits were in 79% of the total Argentine corn crop. The main impact of using the technology on farm profitability has been yield increases. Various studies, (e.g, see ISAAA review in James [64]), have identified an average yield increase in the region of 8% to 10%, from the use of IR cultivars up to 2004. Brookes [65] has indicated that more recent trade source estimates have put the average yield increase in the last 2-3 years to be between 5% and 6% [65].

HT corn was first planted commercially in Argentina in 2004, and by 2010, 47% of the total corn area was planted to varieties containing a HT trait. During the crop marketing years of 2004-2006, biotech traits were only available as a single gene (not stacked with the IR trait) which resulted in limited adoption of HT technology in Argentina up to 2006 [65]. In the ‘Corn Belt’ area, literature indicates that the use of the single trait HT technology has resulted in an average 3% yield improvement via improved weed control [65]. In the more marginal areas, literature indicates that the yield impact has been much more significant (+22%) as farmers have been able to significantly improve weed control levels[65]. In 2007, stacked traits became available and contributed to a significant increase in the HT corn area in subsequent years. In 2010, stacked traited seed accounted for 85% of the total HT area. For stacked traited HT seed the average yield gain identified within the literature since adoption has been +15.75% [65]. Given that the average yield impact for single-traited IR corn identified with early adoption was 5.5%, Brookes [65] applied this level of impact to the IR component of the study, and attributed the balance to the HT trait. Brookes subsequently reported that the assumed yield effect of the HT trait on the area planted to GM stacked corn seed was +10.25% [65].

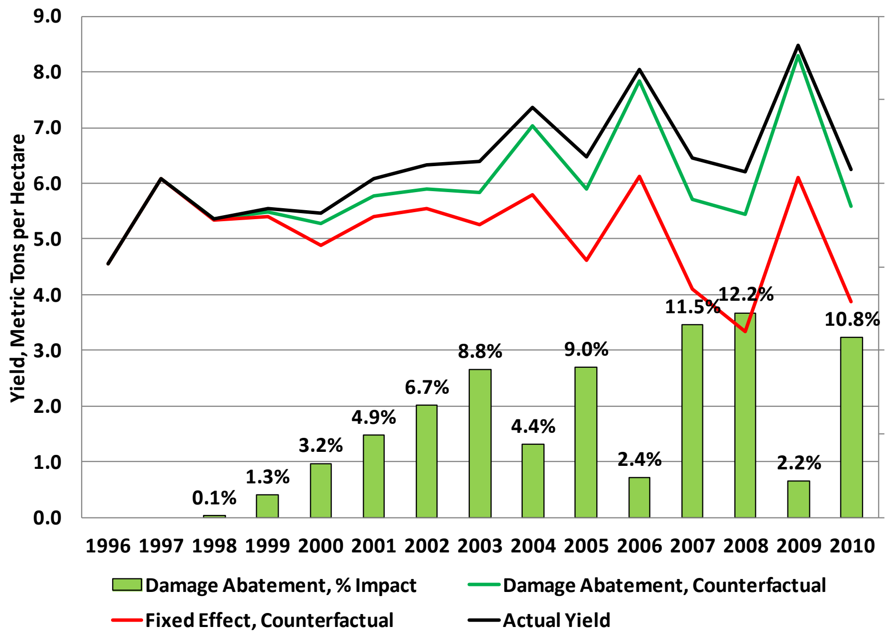

Figure 5. Estimated Argentina Yield Impacts (Metric Tons per Hectare).

As presented in Figure 5 the 2006-2010 average national yield impacts range between 2.5-12.1% which puts them within range of other published findings. Of the biotech adopting regions evaluated the national yield impact predictions for Argentina are the largest and most variable. Large and variable impacts are consistent with prior expectation. Prior to the adoption of IR-CB seed, various insecticides had not traditionally been used in the production of corn in Argentina. In fact, very few farmers had used insecticides targeted at corn boring pests [65]. This lack of conventional treatments supported the relatively larger efficiency gain from the adoption of GM corn. Poor efficacy of the insecticides, the need to get spray timing right (at time of corn borer hatching), seasonal and annual variations in pest pressure and lack of awareness as to the full level of yield damage inflicted by the pests--all supported the comparatively higher proportional increases in Argentine corn yields based on the introduction of IR-CB crops.

As discussed earlier GM corn is assumed to reduce production risk and improve quality of grain. This assumption is most apparent in the predicted yield impacts for Argentina. In 2006 and 2009, ideal climate throughout the Corn Belt and favorable economic conditions in agricultural investment and financial returns increased both corn fertilization and the widespread use of top seed genetics which resulted in record yields. Record efficiency gains realized by the ideal climate significantly lowered the relative contribution accounted for by the GM damage abatement traits. In 2007-2008 the combination of severe drought and the introduction of stacked HT and IR trait packages resulted in significant increases in the predicted yield impacts. The sizable impacts predicted in these years offers strong support to the hypothesis that GM corn significantly lowers aggregate production risk.

The estimates generated from the damage abatement model did support the hypothesis that the adoption of GM corn has significantly increased aggregate yield. However, based on this research the author concludes that impacts generated by [21] are significantly

2.5.4 South Africa

South Africa was the first and remains the primary African country to embrace the GM technology, which was first commercially used in 2000. The technology was widely used in corn accounting for 78% of South Africa's planted area by 2010. HT corn has been grown commercially in South Africa since 2003, and in 2010, 36% of total corn plantings were herbicide tolerant [65]. IR corn has been grown commercially in South Africa since 2000. In 2010, 69% of the country's total corn crop used IR cultivars. The main impact has been an average yield improvement as the cost of the technology has been slightly larger than the average cost savings from no longer applying insecticides to control corn borer pests. Published findings on the farm-level impacts have averaged a yield improvement of between 3.7% and 32.8% in the years 2000-2006, with an overall average of about 15.3%. In 2008 and 2009, previous analysis estimated the yield impact was +10.6% [65].

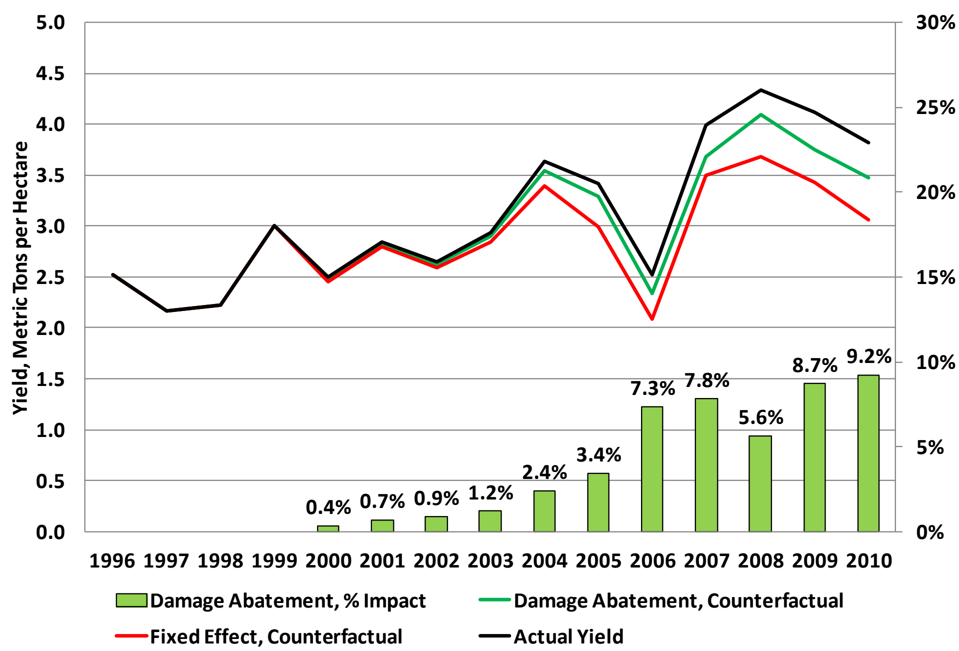

Figure 6. Estimated South African Yield Impacts (Metric Tons per Hectare).

While GM corn had been commercially available since 2000, national adoption levels remained relatively low until 2006; consequently, so too were the predicted national yield impacts. As presented in Figure 6 the 2006-2010 average national yield impacts range between 4.7-7.6% which puts them within range of other published findings. These aggregate impact predictions are near the lower end of previous impacts analysis. However, considering that most GM corn impact assessments were conducted at the farm level and mostly in the least developed regions of South Africa, it is likely that they overstate national average impacts. Furthermore, data on South African hybrid planting densities indicated a significant increase had occurred during the same period, accounting for a significant share of the increases in national yield levels. Nevertheless, one could still hypothesize that had it not been for biotech adoption, the aggregate genetic improvements, as measured by the increase in hybrid planting densities, would not have occurred.

Having reviewed the national yield impacts and determined them to be consistent with prior expectations, the author concludes that biotechnology adoption in South Africa has significantly increased national yields and accepts the predicted impacts as highly plausible reflections of the actual national impacts of biotech corn adoption.

2.5.5 The Philippines

In the Philippines, insect resistant corn was first used commercially in 2003, with herbicide corn also adopted from 2006. HT corn was first grown commercially in 2006, and in 2010 was planted on 20% of the total corn area. Information about the impact of the technology in the first two years of adoption was limited, although it was reported by Brookes [65] that industry sources estimated that, on average farmers using it had derived a 15% increase in yield. More recent analysis by Gonzales [82] identified an average yield gain of +5%. IR corn has been commercially planted in the Philippines since 2003. In 2010, 18% of the Philippines corn area was planted with IR cultivars. Like Argentina, prior to the adoption of IR varieties the use of chemical pest management was not well established. Estimates of the impact of using IR show annual average yield increases in the range of 14.3% to 34% (Gonzales [83], Yorobe [84]). For 2008 onwards a yield impact of +18% has been documented by Gonzales [82].

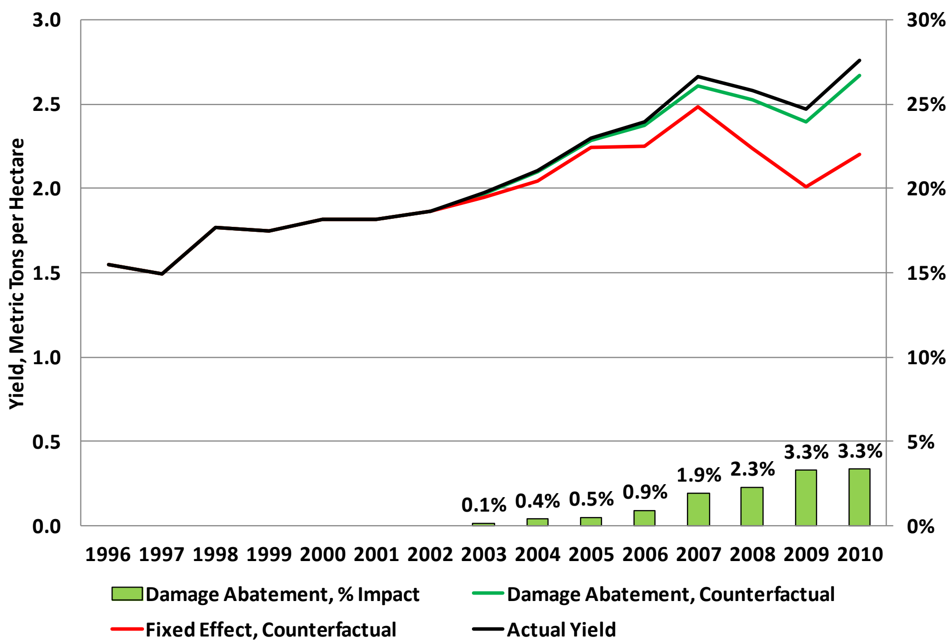

Figure 7. Estimated Philippines Yield Impacts (Metric Tons per Hectare).

As presented in Figure 7 the 2010 average national yield impacts was predicted to be 3.0%. While this appears to be significantly less than the findings documented within the literature, the fact that the published impacts are based on farm-level studies limits their ability to reflect what the impact is at the national level. By 2010 only 21% of corn area used biotech corn. Nevertheless, assuming that the growth in impacts remains constant with the growth in adoption, scaling adoption to 100% would imply that the national impact would be in the neighborhood of 15% which put it into range of farm-level findings. Furthermore, as with South Africa data on hybrid planting densities in the Philippines suggested a significant increase. Over the same period that biotech was introduced, national average hybrid planting densities were reported to have doubled.

The presented impacts indicate strong statistical evidence which supports the author's hypothesis that biotech adoption has significantly increased national yield levels. However, based on this research the author concludes that impacts generated by [21] are significantly overestimated.

2.5.6 Brazil

Brazil is the final biotech adopting region considered in this analysis. Brazil first adopted GM corn in 2008 when IR technology was the first to be introduced. In 2010, 54% of the total crop was planted with IR varieties. The average yield impacts in other studies were +4.66% in 2008 and +7.3% in 2009 [65, 85]. 2010 was the first year in which HT corn was planted in Brazil and covered approximately 4% of that country's corn planted area. Based on analysis by Galvao [85], the technology is estimated to be delivering a yield gain of about 2.5%.

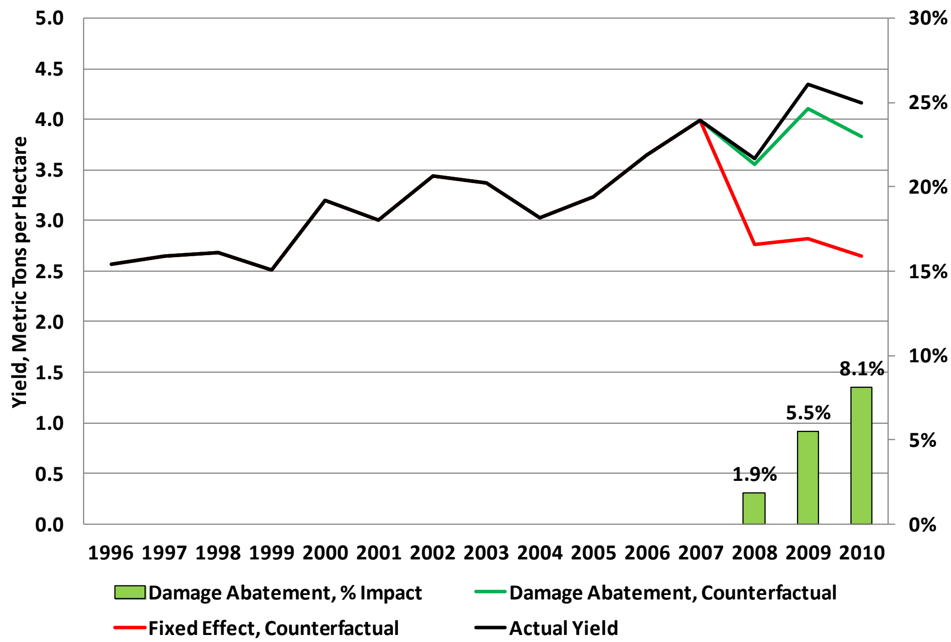

Figure 8. Estimated Brazil Yield Impacts (Metric Tons per Hectare).

As presented in Figure 8, the 2010 national yield impacts was estimated to be 7.4% which puts it within reasonable range of all other published findings. Nevertheless, with only 54% of the area protected, the author sees the predicted national impact as slightly higher than expected. While corn boring pests (notably the Fall Armyworm (*Spodoptera)*) are a major pest problem in Brazilian corn production, approximately 50% of the total annual crop was regularly treated with insecticides targeting this pest (typically five spray treatments/crop) [65].

With 50% of the crop unprotected there is potentially strong support for a larger impact. Furthermore, considering that the Brazilian climate supports relatively higher pest pressures, even if a large amount of the IR corn was adopted in the area that had previously used chemical abatement practices, the superior efficacy of the GM-IR protection relative to manual sprayings leaves substantial room for significant yield increases from reduced inefficiencies.

The agronomic literature indicates that GM-IR protection is much more effective than traditional methods used for controlling pests. In the case of corn borers, pesticides could be expected to provide, at best, only 80% control of first generation larvae and 67% control of second generation larvae [75].

After considering the intensity of the Brazilian pest situation, the author concludes that the national impacts predicted by the damage abatement model are consistent with the situational characteristics of the Brazilian corn production system and accepts the measure as highly plausible for use in assessing the biotech-induced national yield impact. Furthermore, in line with all the other countries evaluated, the estimates generated from the damage abatement model did support the hypothesis that the adoption of GM corn has significantly increased national yield.

2.6 CONCLUSION

This chapter provides the first ever attempt at econometrically applying the damage abatement model to empirically analyze aggregate national level yields. Findings support the hypothesis that biotechnology significantly boosts aggregate national level corn yields in countries where GM corn varieties have been commercially approved and adopted. Evaluation of the estimated technical efficiencies show that over the 15 years of this analysis, biotech corn adopting regions experienced a 19% increase in efficiency where fertilizer, irrigation, and seed were put into production compared to similar countries that did not adopt. Furthermore, assessment of the results indicates empirical consistency with the hypothesis that GM corn is a risk-decreasing technology.

The empirical application of the stochastic frontier production function model with simultaneous estimation of the inefficiency model presented in this analysis utilized a panel of data from national accounts and revealed that the technical efficiencies of each country were significantly impacted by continued penetration of biotechnology adoption. Efforts made to account for national production technology heterogeneity though the inclusion of time varying factor inputs such as fertilizer and planting densities of both saved and hybrid varieties, demonstrated that previous aggregate impacts documented by Sexton and Zilberman [21] were biased upward by specification and the omission of relevant information.

All findings were found to be lower than what was found by Sexton and Zilberman [21]. Nevertheless, this analysis, is likewise constrained by data limitations that prohibit controls for farm-level endogeneity of adoption. Omission of information pertaining to the levels of initial pest pressures as well as the availability and adoption of chemical alternatives within each country's production technology set has likely induced a downward/upward bias in the estimates for regions characterized by high/low pest pressure and limited/non-limited access to insecticides. While attempt was made to control for heterogeneity across the countries' technology set, the author admits that measures taken were limited by data availability and therefore lack optimal levels of comprehension.

Improving the aggregate technical efficiency of corn producers is important and challenging for global development. Further developments in stochastic frontier modeling and the prediction of technical efficiencies of firms will improve the empirical evaluation of aggregate yield impacts of biotechnology.

CHAPTER 3. MARKET IMPACT ASSESSMENT 1996-2010

Abstract

This paper analyzes the ex post international market effects of GM corn adoption in the United States, Canada, Argentina, South Africa, Philippines, and Brazil across the 1996-2010 crop marketing years. Aggregate market effects are computed with a seven-region, single-market partial equilibrium model structured by general equilibrium supply and demand functions. Results indicate that increased global supplies resulting from the adoption of GM corn in these six regions lowered world corn prices by 6.7% in 2010. Had GM corn not been adopted, the impact on world area and consumption was estimated at 3.2 million additional hectares of land brought into corn production and 22.4 million metric tons less corn consumed would have been consumed in 2010. Considering that by 2010 only 25% of global corn area was planted with GM seed varieties, the size of these impacts demonstrate that a significant amount intensive gains remain unrealized by most of the world.

3.1 INTRODUCTION

In 2010 the National Research Council identified the lack of recent market impact assessments as one of the major gaps in the economic research on agricultural biotechnology. While many publication have documented yield gains caused by adoption of genetically engineered crops, these studies have been limited in scope. This limitation has resulted in wide variations in the yield gains attributed to the adoption of GM crops. Uncertainty of the yield gains has limited the ability to quantify the market impacts of GM crops. To date, there has been no rigorous ex-post assessment of the market impacts from the adoption of GM corn technologies.

The aim of this chapter is to determine the aggregate market impacts of the GM corn adoption induced production efficiencies. This study only focuses on the quantifiable market benefits accruing to producers and consumer stakeholders. As such, this analysis does not include the benefits to the input market or the value of non-pecuniary benefits. Given the paucity of market impact assessments of GM corn adoption, this chapter has calibrated an international partial-equilibrium model structured on general-equilibrium supply and demand functions to help fill what literature sees as one of the major gaps in the economic research on agricultural biotechnology.

This chapter hypothesizes that countries with policies that welcome the contributions of biotechnology as measured by the national levels of biotech adoption have in essence: 1) increased the national average net returns for corn farmers, and 2) increased the amount and affordability of food supplies.

3.2 LITERATURE REVIEW

To date, there has been no rigorous ex-post assessment of the market impacts of GM corn technologies' adoption. Brookes and Barfoot [65] recent publication, "GM Crops: Global Socio-Economic and Environmental Impacts 1996-2010," provides perhaps the most comprehensive global assessment of the published evidence of the farm-level economic and production effects. However, the foundational evidence from which they base their analysis is subject to significant variability due to spatial and temporal gaps, methodological inconsistencies, and situational dependence within the published literature. Furthermore, while their assessment made excellent use of the literature to evaluate how GM crop adoption has impacted farm-level production and income, its approach limits their ability to make counterfactual inferences regarding the global economic impacts of adoption.

The closest and, to date, most complete assessment of the market impacts of biotech adoption was published by Brookes, Yu, Tokgoz, and Elobeid [86]. They utilized an international multi-market partial-equilibrium model to assess the ex-ante impact of global production, consumption, trade and prices in the soybean, canola, and corn markets. Their analysis suggests that world prices for corn would likely be 5.8% higher, on average, than 2007 baseline levels if biotechnology was no longer available to growers. Their assumed national corn yield impacts for the U.S., Canada, Argentina, the Philippines, South Africa, and Spain were -2.45%, -2.45%, -5.55%, -0.97%, and -5.1%, respectively.

The analysis of [86] made use of Iowa State University's broad modeling system of the world agricultural economy comprised of the U.S. and international multi-market, partial-equilibrium models to evaluate the ex-ante impacts of assuming all used biotech crops were no longer available post 2007. However, the study does not capture: 1) the market and price impacts of historic adoption levels, 2) market price impacts from changes to the base cost of production, and 3) future trends in biotech adoption post 2007. Furthermore, as with [65] their counterfactual biotech induced yield impact assumptions were based on a limited set of published findings which possessed significant spatial and temporal gaps, methodological inconsistencies, and situational dependencies.

Sexton and Zilberman [21] calibrated a multimarket global partial-equilibrium model to assess the 2008 market impacts of biotechnology adoption. Recognizing the lack of agreement among empiricists on the aggregate impacts of GM crop adoption, they [21] employed panel data methods on the rates of GM crop adoption to econometrically estimate the national level yield impacts. While their estimated 2008 price impact of 24% was by far the largest of the set, their estimated yield gains per adopted acre, 45.6%, was also significantly larger than the Brookes et al. [86] study.

Anderson and Jackson [87] used a comparative static model to assess the price and welfare impacts of trade restrictions on GM crops. Their model assumes GM technology delivers just a one-off increase in total factor productivity for that portion of a crop's area planted to GM varieties. While the yield and cost impact was not explicitly stated for corn, U.S. prices were estimated to decrease by 2%.

Several other studies have estimated the welfare implications of adoption based on stylized assumptions about shifts in supply. These studies, too, have been limited in scope and focused primarily on cotton and soybeans in early periods of adoption. With respect to the market impacts of GM corn adoption, there have only been four studies which have documented an induced world price effect. Table 14 shows the estimates of the effect of GM-crop adoption on corn prices. The price effects are different for each crop and technology and depend on market penetration (extent of adoption) of the new technology, assumed yield impacts, and on the details of the models used (particularly supply and demand parameters).

Table 8. Effects of Global Adoption Biotech Corn on Corn Prices

Technology/Crop	Adopting Area	Price Decline	References
Bt corn (a)	United States, Canada, Argentina	1.94%	Anderson and Jackson, 2005
Bt corn (a)	World	2.09%	Anderson and Jackson, 2005
Bt corn	United States and Canada	2.50%	Fernandez-Cornejo et al., 2007
HR Bt corn	World	4-6% (b)	Brookes et al., 2010
Bt corn	World	24.20% (c)	Sexton and Zilberman, 2010

Note: (a) Adoption rate assumptions vary by country and crop. See details in Anderson and Jackson [87]. (b) U.S. FOB, effective range across the ex ante forecast. See details in Brookes et al., [86]. (c) Average across three scenarios. See details in Sexton and Zilberman [21].

Considering that only Brooks, Yu, Tokgoz, and Elobeid [86] and Sexton and Zilberman [21] identified the yield impacts associated with the price impacts and that there was significant differences between their findings and foundational assumptions, there is significant merit in this author's evaluation of the ex post impact of GM corn adoption on the world price.

3.3 ANALYTICAL FRAMEWORK

The calibrated structural framework used for this analysis combines a detailed model of the effects of biotechnology adoption impacts, as defined in chapter 2, on international corn production, demand and price. Biotechnology-adopting nations are specifically identified to assess their unique national level impacts, but are linked back to the rest of the world through market clearing equilibrium relationships to determine their impact on world price.

For the adopting nations, the model uses national information on supply, demand, price, and the levels of biotech adoption; however, the model imposes simplifying assumptions to reduce the multi-market complexities of the model structure. This approach conceptually mirrors that of Sumner [88] and Brookes, Yu, Tokgoz, and

Elobeid [86] as it uses a multi-country simulation framework that is calibrated to replicate historical data on prices and quantities of corn under actual supply and demand conditions. However, this model's exogenous treatment of cross-commodity relations is a departure from prior [88] and [86] approaches, which was necessary to preserve the uniqueness of the welfare assessment respective to the international corn market.

A complete welfare analysis, which takes into account all information related to changes in the market of interest as well as all the information related to changes in related markets, requires large amounts of data thus limiting the feasibility of complete welfare analysis. Due to such feasibility constraints, partial welfare measures, which offer needed flexibility, can be used to complete the analysis. Nevertheless, the way in which partial measures ignore the complex interrelationships with other product and factor markets in the economy necessitates the use of strong assumptions to justify its use.

A conventional partial-equilibrium analysis of a welfare change in the corn market will reflect induced shifts in demand for soybeans but will still be correct so long as the soybean price is exogenous. It would be incorrect, however, if the soybean price is affected, and it will be complicated further when there is feedback from the soybean market into the supply or demand in the corn market. There are two correct ways to measure welfare effects when there are multiple price changes and cross-price effects induced by a supply shift in one market [17]:

1. Add up effects across markets using the welfare areas measured off ceteris paribus supply-and-demand curves in all of the affected markets, all of which may shift as a consequence of an exogenous supply (or demand) shift; it will be correct (and path-independent) only if integrability conditions are met;

2. Use the mutatis mutandis supply-and-demand curves of any of the curves for the commodities of interest, in which case there are no endogenous shifts of any of the curves, and there is no need to add up across related markets [17].

Considering that the objective of this research is to evaluate the economic welfare gained from the adoption of biotech corn, this author invokes mutatis mutandis (general-equilibrium) welfare measures wherein general-equilibrium effects will be captured in a single-market model.

The concept of elasticity in the traditional Marshallian demand curve permits specifying changes in the quantity of a commodity demanded in response to changes in its price, assuming that income and prices of other commodities remain constant. However, the other prices usually cannot remain constant in a free market situation because prices of related commodities are mutually determined. The elasticity of demand, therefore, is an inadequate basis for predicting actual market behavior as noted as early as 1958 by Buse [89].

To account for the inadequacies of the Marshallian demand curve, Buse described the "total demand curve," which he defined as the schedule of quantities that will be demanded as the price of the commodity under consideration varies, allowing the prices and quantities of complements and substitutes to vary as the market system requires [89]. This implies that the measure of the responsiveness of quantity to price represents the "total" elasticity of demand. In essence the "total" elasticity is equal to the Marshallian elasticity obtained holding the price of other goods constant, ${}^{\partial Q_i}/{}_{\partial P_i}$, plus a term reflecting the effect of induced cross-price changes and their effects on the demand for the good in question:

$$\frac{\partial Q_i}{\partial P_i} = \frac{\partial Q_i}{\partial P_i} + \frac{\partial P_j}{\partial P_i}\frac{\partial Q_i}{\partial P_j} \qquad \textit{Eq. 3.1}$$

Buse’s total demand response curve is now more commonly referred to as general-equilibrium demand functions. A general-equilibrium (mutatis mutandis) demand function shows how consumption of a good responds to changes in its own-price, allowing prices of other related goods to adjust in response to own-price changes and allowing the ceteris paribus demand for the good to shift in response to induced changes in prices of related goods [17]. The elasticity of this type of general-equilibrium demand curve corresponds to the “total elasticity” concept introduced by Buse [89]. Similar logic also applies for the supply-side counterpart, wherein an allowance is made for induced changes in the price of related products to feed back into the supply curve of interest.

Alston et. al. [17] indicated that Just, Hueth and Schmitz [90] said it best when they stated: “Net social welfare effects over the economy as a whole of intervention in any single market can be measured completely in that market using equilibrium supply and demand curves of sufficient generality.” Thus, a single-market model *can* measure the full general equilibrium effects. Therefore, this research’s model separates itself from that of Brookes et al. [86] in that this author’s partial equilibrium model will be structured off of “total” general-equilibrium (mutatis mutandis) supply and demand functions.

The total own-price elasticity assumptions calibrated according to Equation 3.1 are specified to reflect the own-price responses which are conditioned by other market activities such as substitution effects. For example, assuming a 1% increase in corn prices would result in something less than a 1% increase in soybean meal prices; if a corn feed demand model was a function of only the price of corn and the price of soybean meal, and the model reported that corn feed demand had an own-price elasticity of -0.20 and a soybean meal cross-price elasticity of 0.10, the "true" total own-price effect would be something between -0.10 and -0.20. This conditioned total own-price elasticity helps to control for some of the general equilibrium feedback that would be expected within a structure that fully endogenizes such cross-price relationships as shown in FAPRI and USDA models. While this dissertation's model does not show the net effect on producers and consumers of various commodities it assumes that optimality conditions are fulfilled elsewhere in the economy [17]. This method provides a way to give reasonable estimates of the overall welfare impacts, while remaining compliant to the strong single market welfare assumptions.

Understanding that the intent for this model was to investigate the aggregate impacts of biotechnology adoption in the corn markets only, disaggregation was kept to a minimum. Regional disaggregation was limited to the United States, Canada, Argentina, Brazil, the Philippines, South Africa, and Rest of World (ROW). Furthermore, this research methodology also minimized the conceptual disaggregation of total supply and total demand to that which sufficiently models aggregate counterfactual behavior. For each region area harvested, domestic consumption, and ending stocks are the only structural components endogenized in the model. The remaining structural components (production, net-exports, and market clearing conditions) are linked via algebraic identities. All yield-related shocks will be exogenously determined from the stochastic frontier analysis developed in chapter 2.

Figure 9 provides a illustration of the structural relationships assumed for each region in the analysis. For simplicity Figure 9 is composed of only three regions. Within each region the top half of the flow chart contains the supply side and the lower half contains the demand side with the final box (Net-Exports) representing the excess supply or demand for each region. World market prices are determined by requiring that the sum of global net exports must equal zero. If region A's supply suffers shocks by adverse weather, the effects of the supply shock will limit A's ability to satisfy the rest of the world's excess demand causing a global equilibrium displacement in the trade balance (determined in the Net Export box of region A). Trade imbalance translates into an increase world price which is transmitted back to each country in the form of an incentive to produce more and/or a rationing signal for demand. The circulation of information within the world market continues until trade balance is restored. The robustness of the model depends both on how the model is structured and how each component of the structure is specified. The operating behavioral assumptions of the agents in the system are that they seek to maximize profit and/or utility.

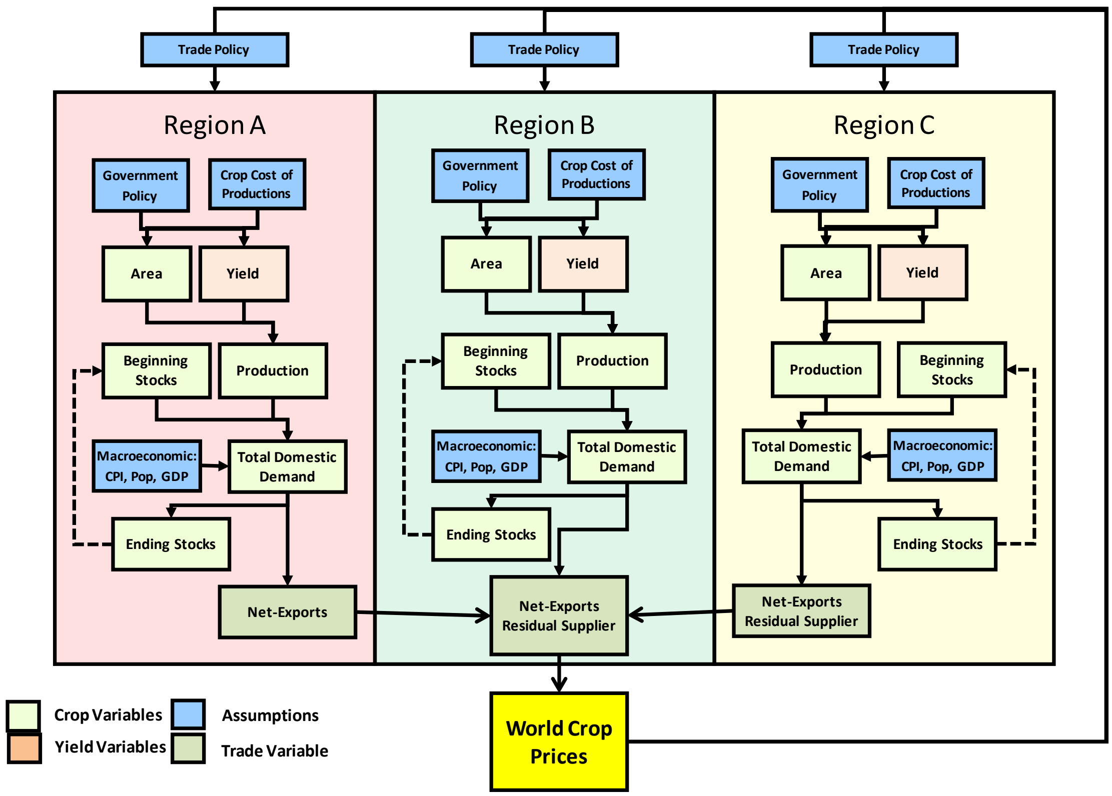

Figure 9. Three Region Single-Market Supply and Demand Flow Chart.

The model includes behavioral equations for area harvested on the supply side, and per-capita consumption and ending stocks on the demand side. Equilibrium prices, quantities, and net trade are determined by equating excess supply and excess demand across countries and regions. The year-to-year market-clearing equilibrium resulting from a supply shock requires that the adjusted quantity supplied equals the quantity demanded to determine the competitive price. In countries where domestic prices were available, these prices are modeled as a function of the world price using price transmission equations. A unit elasticity constraint was imposed on the domestic-to-world price transmission equations to preserve global response consistency across all regions modeled. Once an equilibrium displacing shock is exogenously introduced into the linear supply function, at historical supply prices, for each year a Newton-Raphson type iteration iteratively solves for a new linearized competitive equilibrium.

3.4 DATA

Data for this analysis was compiled primarily from the United States Department of Agriculture's (USDA) Foreign Agricultural Services (FAS)[91]. All production, supply, and distribution data was gathered from the FAS. FAS regularly updates crop supply and utilization data every month for the majority of global market participants. The data reported by the USDA is based on official estimates from the U. S. government. The model uses real prices, derived by deflating nominal prices by the country's consumer price index (CPI). All prices, macroeconomic and cost of production data was compiled from the Information Handling Services' (IHS) Global Insight Country Intelligence (IHS-CI) database and quarterly international Cost of Production (IHS-COP) report, respectively [92-93]. Table 9 lists explicitly all countries covered and variables considered along with sources.

Table 9. Concept and Country Coverage

Country Coverage
United States
Argentina
Brazil
South Africa
Philippines
Rest Of World*

Supply/Demand Quantities	Source
Area Harvested	FAS
Yield	FAS
Production	FAS
Domestic Consumption	FAS
Ending Stocks	FAS
Exports	FAS
Imports	FAS
Corn Farm Price	IHS

Prices/Cost Data	Source
Corn Farm Price	IHS-COP
Labor cost	IHS-COP
Seed Cost	IHS-COP
Chemical Cost	IHS-COP
Fertilizer Cost	IHS-COP

Macroeconomic	Source
Real GDP Levels, Annual (Billions of 2005 U.S. dollars)	IHS-CI
CPI Inflation, Annual (Indexed, 2000=100)	IHS-CI
Exchange Rate, Annual Average (Local Currancy per U.S. dollar)	IHS-CI
Population, (Millions of persons)	IHS-CI

* No explicit Price or Cost data is included for ROW. Also, ROW use World CPI as a price deflator

ROW was calculated for each supply and demand variable as World minus the sum of Argentina, Canada, Republic of the Philippines, South Africa, and the United States. Since there are six regional breakouts and three structural components (Area Harvested, Domestic Consumption, and Ending Stocks) from each region chosen to be endogenized, the model is comprised of 18 behavioral equations and a number of accounting identities that are used to determine model equilibrium.

The following section take a closer look at each of the three structural components endogenized into the model by; a) providing a general overview of the behavioral assumptions, b) presenting the selected specifications, and then c) providing an overview of the elasticities found within the literature along with the elasticities selected to stylize the specification within the partial equilibrium model.

3.5 MODEL SPECIFICATION

Considering that the objective of this research is single market aggregate response, the conceptual classification of the following specifications fall within the "directly estimated" or partial, commodity response models. One of the essential characteristics of this class of models, in the circumstance where agricultural production/consumption is described by multiple outputs/inputs, is that they are of a partial nature. This significantly limits the role which the theory of the firm can play in the specification and estimation of the models, and minimizes the scope for exerting the profit/utility maximizing conditions as restrictions upon the supply/demand equations. The theoretical underpinning of this class of models is of an *ad hoc* nature and derives largely from the fact that these models are based on time-series data in which supply/demand response is measured at an aggregate (i.e., national) level.

While there exists major problems with the single-commodity reduced-from-response analysis, the same is also true of its highly restrictive and static competitors. It remains the case that aggregate reduced-form analysis is the most used and preferred of the methods. The most significant factors in its favor are that it operates directly upon the aggregate supply data which is the object of interest for projection purposes, and that it handles dynamic adjustments to supply/demand while other procedures do not. Such specification also minimizes the capacity for specification errors to accumulate through successive stages. Finally, and perhaps most significantly, it is a technique which has shown itself capable of generating acceptable and useful results.

3.5.1 AREA MODEL

Since production in any period is not instantaneous, and is in any case dependent upon past investment decisions, the production observed in any period tends to be affected greatly by past decisions. These are expected to be a function of both economic conditions prevailing at the time key decisions were made (e.g., to plant a crop) and of expectations about future conditions. Therefore, an evaluation requires the formulation of expectations and development of functional forms, variables, and estimating procedures to incorporate the various postulated expectation generators. Developments in this area have proceeded from the theories of Koyck [94] and Nerlove [95] through flexible distributed lags of the Almon [96] type to the rational expectations of Muth [97]. The integration of expectation variables for price, revenue or profits into supply functions represents a reduced-form method of allowing for the role of investment in supply response.

The central issue to an area response decision is that it is taken before post harvest output price are known. Price expectations are defined to capture the producer's rational on pre-planting net return expectations. Several models have been documented within the literature to capture the expectation components [98-102]. Despite the many contributions, this research relies on the Nerlove partial adjustment model. By employing the partial adjustment, the author is able to parsimoniously capture both the short- and long-run dynamics of the behavioral specification. Partial adjustment follows the idea that farmers are not able to move to equilibrium immediately because of temporary fixities in assets. Therefore the desired area response, a_t^*, is restricted by the partial adjustment coefficient. The partial adjustment is structured as

$$a_t - a_{t-1} = \delta(a_t^* - a_{t-1}), 0 \leq \delta \leq 1 \qquad \textit{Eq. 3.2}$$

where δ is the partial adjustment coefficient, which decreases the speed of the asset adjustment process.

Common criticisms of the partial adjustment approach are: a) constant ad-hoc adjustment coefficients b) assumes only information available to the producer is previous prices c) ignores effects of government policies (anticipated policy changes that affect price formation, e.g., the "Lucas critique") d) ignores "general equilibrium" effects such as changes in input/output prices and changes in factor prices.

The net returns specification does, however, loosen the criticized restrictiveness of the Nerlove model as it allows additional information that is known by the producer to be included in the total area allocation model. It allows information on current variable costs of production and policy parameters to affect expected returns. Furthermore, considering that the ex-post hypothesis of this thesis is that a production input has increased producer and consumer welfare, the counterfactual scenario assumes producers could fully anticipate the market impacts from the adoption level of GM corn. For these reasons, this dissertation structures the net-returns specification as being a function of a modified naïve price expectation. Naïve price expectations have been modified, so that when a shock changes the model solution of prices each year, the supply side of the model is able to "see" those price changes right away in *t* instead of waiting until *t*+1. Unlike price changes caused by unforeseeable factors such as post-planting weather, a limit on a factor input such as biotechnology would fall in the category of "something farmers should be able to anticipate," as it affects preproduction decisions; thus, there is no reason to have producers only respond a year later. This modification forces perfect elasticity between price changes in year *t* and price expectations for year *t*.

The modifications in naïve price expectation is calculated as

$$E(P^*_{i,t}) = \begin{cases} P^0_{i,t-1}, & iff\ P^*_{w,t} = P^0_{w,t} \\ P^0_{i,t-1} * [1 + \left(\frac{P^*_{w,t} - P^0_{w,t}}{P^0_{w,t}}\right)], & iff\ P^*_{w,t} \neq P^0_{w,t} \end{cases} \qquad \textit{Eq. 3.3}$$

where

1. $E(P_{i,t})$ is the pre-planting expectation of post harvest output price for country i in year t,

2. $P^0_{i,t-1}$ is the actual historic output price received in country i in year $t-1$. This lagged price represents the naïve portion of the formulated expectation.

3. $P^0_{w,t}$ is the actual historic world price in year t,

4. $P^*_{w,t}$ is the counterfactual world price in year t.

In addition to the modified naïve expectation formulation, further commentary is required in regard to the fixed use of the lagged "domestic" prices multiplied by the percent change in “world” prices. Throughout both the supply and demand structure of the model, real local currency domestic prices are employed in all regions where domestic farm prices are available. The author makes use of domestic prices to maintain consistent scaling with the domestic variable cost data.

To ensure consistency with the modified naïve price expectation formulation, the modified price transmission preserves the same functional form. Domestic prices reported in local currency per metric ton have been selected to represent local market conditions. To allow for communication between domestic and rest-of-world competitive market signals, a modified price transmission formulation is included to ensure that the elasticity of domestic prices with respect to world price is consistently unit elastic. Consistent with Equation 3.3 the modified price transmission preserves the same functional form as follows:

$$P_{i,t}^{*} = \begin{cases} P_{i,}^{0}, & iff\ P_{w,t}^{*} = P_{w,t}^{0} \\ P_{i,t}^{0}(\frac{P_{w,t}^{*} - P_{w,t}^{0}}{P_{w,t}^{0}}), & iff\ P_{w,t}^{*} \neq P_{w,t}^{0} \end{cases} \qquad \textit{Eq. 3.4}$$

where

1. $P_{i,t}^{*}$ is the counterfactual domestic price for country i in year t,

2. $P_{i,t}^{0}$ is the actual historic price paid in country i in t,

3. $P_{w,t}^{0}$ is the actual historic world price in year t,

4. $P_{w,t}^{*}$ is the counterfactual world price in year t.

The total area allocation model presented in this section ignores all policy information. While a number of studies, summarized in Alston and Martin [103], explain how the interaction between price-distorting policies and research-induced technical change may affect the size and distribution of welfare changes, an application of the Lucas [104] critique to this type of analysis could give rise to concerns that estimated elasticities are not necessarily robust to changes in policy regime [105]. The lack of comprehensive, consistent and comparable time series data on policy distortions across all producing countries significantly limits its integration. This limitation, more or less, constrains this analysis to proceed on the assumption that price transmission elasticities do not change "too much" as a result of a Lucas type effect.

The last component of the area specification that needs to be addressed is the cost of production values used within the specification. All costs of production data were collected from IHS Global Insight's Cost of Production (COP) study [92]. The COP study contains itemized national and sub-national variable and fixed expenses. Costs in this study are defined by the per acre direct operational cost of corn production per hectare. Direct operational costs pulled from the COP study include seed, fertilizer, chemicals, fuel, and labor variable costs. Direct operational costs are reported as real local currency cost per hectare. While the COP is the only comprehensive source for national average COP data by crop, it is, however, compiled from many different governmental sources which are not always consistently updated. To control for some of the noise within the data set, the author calculated the three year moving average of each time series. Figure 10 presents the averaged direct operational cost data series for the primary biotech adopting region of interest.

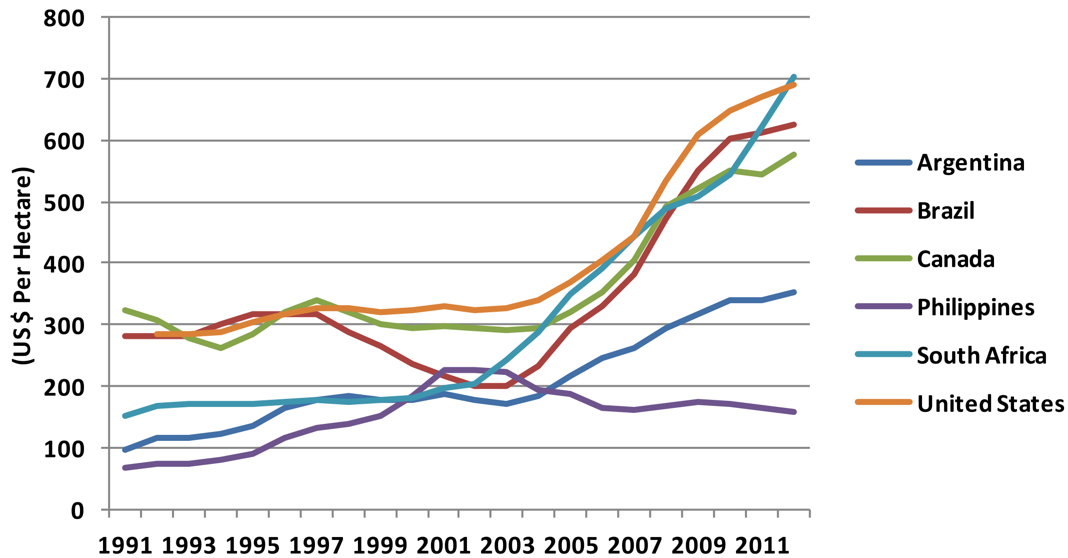

Figure 10. National Corn Operational Cost of Production.

For simplicity of analysis, fixed costs have not been included as they are assumed to be related to capital purchases. By assuming producers already own the proper capital for crop production, this implies that investment decisions were made in previous periods, so the stock of capital in any given period is essentially predetermined. Figure 11 presents the nominal base net return variables in U.S. dollars per hectare.

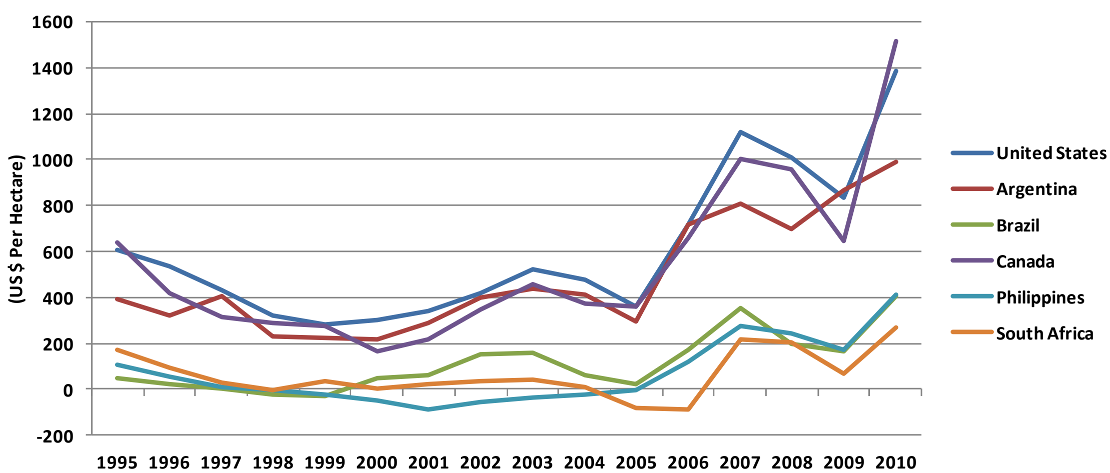

Figure 11. National Corn Net Returns of GM Adopting Regions (U.S.$ per Hectare).

Due to the lack of available data on the planted area, the harvested area is used in the area response function. The area allocation equation selected for this analysis is as follows:

$$a_{i,t} = f(a_{i,t-1}, \pi_{i,t}^{*}) \qquad \textit{Eq.3.5}$$

$$= \beta_0 + \beta_1(a_{i,t-1}) + \beta_2(\pi_{i,t}^{*})$$

where

$$\pi_{i,t}^{*} = P_{i,t}^{*} * Y_{i,t}^{*} - C_{i,t} \qquad \textit{Eq. 3.6}$$

Variables in equations 3.6 and 3.7 are defined as:

1. $a_{i,t}$ is the area harvested in country i at time t,
2. $a_{i,t-1}$ is the area harvested in country i at time $t-1$,
3. $\pi_{i,t}^{*}$ is the expected net-returns in country i at time t,
4. $P_{i,t}^{*}$ represents the farmers pre-planting expectation of post harvest corn prices,
5. $Y_{i,t}^{*}$ represents the farmers pre-planting expectation of post harvest corn yields, and
6. $C_{i,t}$ is the variable cost of corn production.

This specification deviates slightly from classical production theory, as the net return specification is not theoretically consistent with the profit maximization behavioral postulate. Using a net returns specification implies Constant Returns to Scale (CRS).

By assuming CRS, the profit function is not globally concave thereby violating uniqueness of the solution which deems it inconsistent with the profit maximization behavioral postulate [106]. Nevertheless, due to uncertainties regarding effective yields, farmers cannot precisely know their production function the net returns approach, has been considered as an applicably more realistic tool than a strict profit maximization postulate (Collins and Taylor [107], Davison and Crowder [108]). Furthermore, the net returns specification provides for a more flexible functional form as it uses a single variable to capture changes in prices, yield expectations and production costs.

As discussed earlier, all supply and demand functions structured for the author's welfare evaluation will be structured and calibrated as strict single-market general-equilibrium supply and demand functions. The author accepts the three partial-equilibrium postulates defended by Harberger [109] and follows the work of Buse [89] by structuring Equation 3.5 off of total elasticity assumptions. This allows the author to define Equation 3.5 as the schedule of areas that will be allocated as the price of the commodity under consideration varies. Therefore, prices and quantities of complements and substitutes can, conceptually, vary as the market system requires. This implies that the measure of the responsiveness of corn area to price represents the "total" corn net returns elasticity.

$$\frac{\partial a_{i,t}}{\partial \pi^*_{i,t}} = \frac{\partial a_{i,t}}{\partial \pi^*_{i,t}} + \frac{\partial \pi^*_{j,t}}{\partial \pi^*_{i,t}} \frac{\partial a_{i,t}}{\partial \pi^*_{j,t}} \qquad \textit{Eq. 3.7}$$

The area elasticity, $\frac{\partial a_{i,t}}{\partial \pi^*_{i,t}}$, is then equal to the own-return elasticity obtained holding the returns of other commodities constant, $\frac{\partial a_{i,t}}{\partial \pi^*_{i,t}}$, plus a term reflecting the effect of induced cross-price changes and their effects on the allocation of the area in question, $\frac{\partial \pi^*_{j,t}}{\partial \pi^*_{i,t}} \frac{\partial a_{i,t}}{\partial \pi^*_{j,t}}$. Defining equation 3.5 as a total area allocation equation offers sufficient generality to assume that it completely measures the effects of intervention in the corn market alone [90].

Considering the restrictive nature of the area equation, in that it is only a function of expected net returns and lagged area allocation, the author looks to the literature for elasticity assumptions. The use of documented elasticities is a common practice within policy and welfare analysis [88], [12, 110], [5, 111], [10], and [112].

Shepherd [105] stressed that the trick to using documented elasticity is in finding one that corresponded to the function in which it will be applied. Although the functional forms used in this paper are intentionally simple and general, it did not perfectly correspond with any functional form used to estimate the elasticities found within the literature. To justify the use of documented elasticity estimates within this model, one must determine whether the functional forms used in estimation are sufficiently close to those used within this dissertation's unique model. Table 10 presents several elasticity estimates documented in the literature.

Table 10. Documented Area Elasticities within the Literature

	Own	Own	Cross - A	Cross - B	Cross - C	Cross - D	Cross - A+B+C+D	
	Short-Run	Long-Run	Short-Run	Short-Run	Short-Run	Short-Run	Short-Run	Sources
United States	0.219	N/A	-0.176	-0.043			-0.219	Bridges and Tenkorang (2009)
	0.22	?	?					Whittaker and Bancroft (1979)
	0.34-0.56	0.93-2.07	?					Reed and Riggins (1981)
	0.12 - 0.17	?	?					Ryan and Abel (1972)
	0.158	0.158	-0.15				-0.15	Chavas and Holt (1990)
	0.156	0.156	-0.07	-0.09			-0.16	Chembezi and Womack (1992)
	0.51	1.17	-0.12	-0.345			-0.465	Huang and Khanna (2010)
	0.17	0.17	-0.17				-0.17	Lin and Dismukes (2007)
	0.293	0.293	-0.145	-0.065	-0.028	-0.01	-0.248	Lin et al. (2000)
	0.293	0.293	-0.203	-0.018			-0.221	Lin et al. (2000)
	0.372	0.372	-0.213				-0.213	Adams (1996)
	0.248	0.248	-0.164	-0.056			-0.22	Lin et al. (2000)
	0.18							Nerlove (1956)
	0.95	?	-0.45				-0.45	Miller and Plantinga (1999)
	0.31	**0.48**					**-0.25**	**Mean**
Argentina	0.21	2.1	?					Martin (1998)
	0.7	?	?					CARD model
	0.46	**2.10**					**?**	**Mean**
Brazil	0.42	?	?					CARD model
	0.42	**?**					**?**	**Mean**
Canada	0.57	7.94	-0.33	-0.24			-0.57	Weersink (2010)
	0.26	0.26	-0.21				-0.21	FAPRI, Bahrenian et al. (1986)
	0.18	?	?					CARD model
	0.34	**4.10**					**-0.39**	**Mean**
Philippines	0.51	0.63	?					Nasol (1982)
	0.81	4.26	0.23	-0.45			-0.22	Cardenas et al. (2005)
	0.66	**2.45**					**-0.22**	**Mean**
South Africa	0.12	0.46	?					Poonyth et al. (2000)
	0.28	?	?					CARD model
	0.20	0.46					**?**	**Mean**

It is apparent that even within the literature, there is a significant amount of variation across the documented estimates. Having comprehensively reviewed documented estimates, the question then becomes how best to take account for the uncertainty surrounding elasticity estimates.

Several of the U.S. elasticities documented in Table 10 are derived from specifications that have imposed programming and econometric restrictions to remain consistent with profit and utility optimization at the firm level. Such restrictions complicate the total area elasticity calculation. A cost of imposing such restrictions is that the dynamics of supply are suppressed, and the estimated responses indicate changes from one equilibrium position to another (Colman, [113]).

For example if one was to assume a fixed area constraint and that all other commodity net returns or prices would change by 1% in response to a 1% change in corn net returns or price then holding all else constant the total area allocation elasticity with respect to corn price would be zero. The author recognizes that neither of these assumptions is likely to hold as competing crop prices should increase when corn prices increase, but not by the same proportion. Using the estimates presented in Table 10, the author calculates the average own and cross price elasticities across all methodologies (restricted and directly estimated). In the U.S., the average own-price elasticity becomes 0.31 while the average cross-price becomes -0.25 indicating that corn area would increase by 0.06% if all crop prices increased by 1%. Cross price effects generally lower the magnitude of area price elasticities when all prices are allowed to adjust [114], but the correlation between own and cross-prices is not expected to be one.

The author, therefore, assumes a total area response elasticity of 0.10 which incorporates the fact that cross-prices will generally change by less than 1% when corn prices change by 1%.

A second problematic situation arises from the fact that there is very little documentation on the long-run elasticity. Having structured Equation 3.5 as a partial adjustment model, long-run elasticity is expected to be as much if not more important than short-run elasticity over the ten year welfare evaluation timeframe. Calculating the average of available estimates, the author finds that on average the long-run elasticity is over six times the short-run elasticity. However, this average does not include the CARD elasticities within the average due to uncertainty regarding long-run elasticities in the CARD system. Considering the small sample size, the author assumes a long-run elasticity that is four times the short-run elasticity, suggesting a coefficient on the lagged dependent variable of 0.75.

After careful consideration of the empirical constraints, this research's methodology defaulted to the simplest possible solution: Assume the same short- and long-run net-return elasticity across all countries of interest. Table 11 presents the assumed short- and long-run total corn area allocation elasticities.

Table 11. Selected Elasticity Assumptions for Model

Region	Elasticity	W.R.T.	SR	LR
United States	Area Harvested	NetReturn Real LC/MT	0.06	0.24
Canada	Area Harvested	NetReturn Real LC/MT	0.06	0.24
Brazil	Area Harvested	NetReturn Real LC/MT	0.06	0.24
Argentina	Area Harvested	NetReturn Real LC/MT	0.06	0.24
South Africa	Area Harvested	NetReturn Real LC/MT	0.06	0.24
Philippines	Area Harvested	NetReturn Real LC/MT	0.06	0.24
ROW	Area Harvested	US FOB, Real $/MT (t-1)	0.07	0.53

Note: ROW = rest of the world.

Long-run elasticities for the six countries of interest are assumed to be 4x the size of the short run. The long-run elasticity of 0.24 is significantly lower than the long-run estimates documented in the literature where national averages ranged from 0.43 to 4.10 (see Table 10). To impose long-run elasticities that were four times the size of the short-run elasticities, the partial adjustment coefficients were all assumed to be 0.75. Since Equation 3.5 is specified as a linear functional form, a coefficient of 0.75 implies that with price shocks, equilibrium adjustments in area allocations occur for many years. Reasons for this include investment lags, firm growth, market entry, technology changes, and other market rigidities which influence long-run output supply and input demand decisions.

While this dissertation’s assumed elasticities are reported with respect to net-returns, to better illustrate the seemingly arbitrary selection of 0.06 as a short-run elasticity and to improve comparability with Table 11 and the suggested own-price elasticity calibration target of 0.10, Table 12 converts the net-return elasticities into price elasticities. Conversions are calculated by: 1) exogenously imposing a sustained 10% increase in world corn prices holding costs and expected yields constant; the result is then divided by 0.1 to obtain the percentage change in expected net returns with respect to a 1% change in price, ε_P^{NR}, 2) calculating area elasticity with respect to net-returns, ε_{NR}^{A}, and 3) finally solving for the area elasticity with respect to price by multiplying the two previous elasticities, $\varepsilon_P^{A} = \varepsilon_P^{NR} * \varepsilon_{NR}^{A}$. Tables 12 present the responses expected corn net returns from a sustained 1% increase in price.

Table 12. Response in Expected Corn Net Returns Elasticity With Respect To Sustained 1% Increase in World Price

	1996 Response	2000 Response	2010 Response
United States	1.5	1.9	1.8
Argentina	1.2	1.6	1.7
Brazil	2.5	3.6	3
Canada	1.6	2.8	2.1
Philippines	1.4	3.5	1.6
South Africa	1.7	3.1	1.9

Variation in the implied expected corn net return elasticities with respect to changes in world price are a direct reflection of the author's assumptions regarding the cost of production. The greater the cost of production relative to the expected gross returns the lower the net returns. The lower the net returns the larger the net returns response to a change in the expected price.

Table 13. Response in Area Harvested w.r.t. Sustained 10% Increase in World Price

	1996 Response	2010 Response	Average of Published Findings Short-Run	Long-Run
United States	0.12	0.46	0.31	0.48
Argentina	0.07	0.39	0.46	2.10
Brazil	0.10	0.57	0.42	
Canada	0.19	0.55	0.34	4.10
Philippines	0.12	0.55	0.66	2.45
South Africa	0.06	0.76	0.20	0.46
ROW	0.07	0.53		
World	0.13	0.47		

Note:

As illustrated in Table 13, implied short-run area elasticities, ε_P^A, (found in year 1996 for the six country breakouts) are significantly larger than those presented Table 11 and are near the 0.10 target.

Assuming a target 2000-2010 series average short-run net-return elasticity of 0.06 for all area equations insured that own-price effects were consistently lower than the elasticities documented in the literature. Table 13, however, indicates that imposed consistency has not transcribed to the price elasticities. The slight variation is a direct consequence of the relative cost assumptions imposed by net-returns specification. Large elasticities are reflective of regions where per-unit variable costs are high relative to output prices, while lower elasticities are from regions where the opposite is true.

3.5.2 DEMAND MODEL

The regional levels of consumption illustrated in Figure 12 indicate that over 90% of world corn is consumed in the United States and ROW regions.

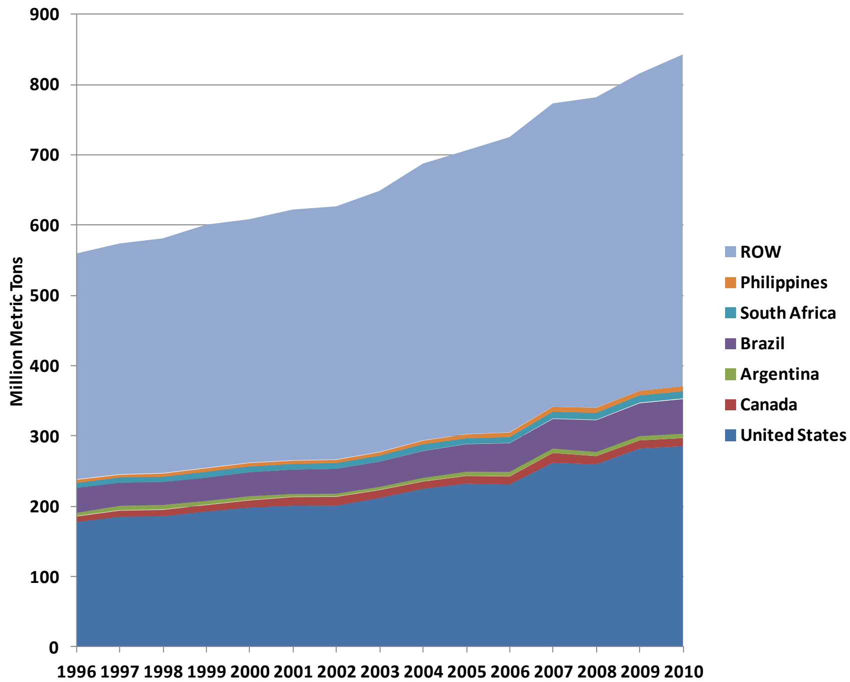

Figure 12. 1996-2010 Growth in Total Corn Consumption.

During the 1996-2010 marketing years the world demand for corn has grown by nearly 40%. More than 90% of the growth originated from the United States (38%) and the ROW (53%) regions.

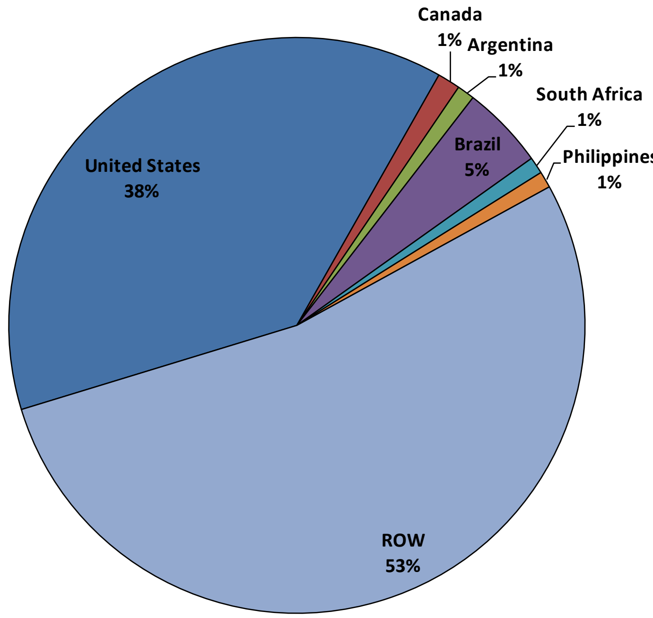

Figure 13. Regional Share of the 1996-2010 Growth in World Corn Consumption.

In order to properly specify total domestic consumption, $D_{i,t}$, it is important to first understand what it represents within the partial equilibrium model. The following briefly describes the characteristics of each aggregated component followed by the stylized specification assumed for this analysis. $D_{i,t}$ is an aggregation of food, feed, seed, residual, and industrial uses.

Food use is an aggregate of corn glucose and dextrose use, plus starch use, beverage alcohol, cereals, and other uses. Economic theory suggests that the quantity demanded of corn for food use is a function of its own-price, price of substitute goods, income, and population. Food use for all crops depends on both own price and competing crop prices as well as consumer expenditures.

Previous research of per capita corn food consumption data has suggested three important things about the quantity of corn demanded for food. First, changes in consumer income have little or no effect on per capita food consumption, i.e., the income effect is small. Second, and as a consequence of the first, the total domestic demand for food has varied directly with population. Third, the aggregate consumer demand for food is highly unresponsive to price, suggesting that domestic demand for food is highly inelastic. The explanation for the price inelasticity of the total food demand is simplified by two biological constraints. First, the biological requirements in the human stomach are limited by how much food it can ingest per period of time. Second, food has few close substitutes [115].

Feed and residual use account for the largest percent of total corn consumed within the crop marketing year. The feed demand equation is theoretically categorized as a derived demand function in which the demand for feed is generated entirely through the demand for meat. Regarding feed use: changes in corn prices result in changes in livestock production, and basic biology means that all of the changes in animal inventories do not occur in period t. Thus, even if feed rations were completely unaffected, changes in corn feed use would take years to fully play out.

Ethanol use, as with the feed demand specification, is also categorized as a derived demand. While ethanol production is primarily a U.S. demand factor, special consideration is warranted due to its policy-based characteristics which separate it from other demand factors. In 2010, 27% of U.S. corn production was used to make ethanol for blending with gasoline, up from 10% in 2005. The rapid growth was largely attributed to federal mandates through the Renewable Fuel Standard (RFS). RFS required a minimum quantity of ethanol content in gasoline. The RFS was introduced in the 2005 U.S. Energy Policy Act. In 2007, under the provisions of the U.S. Energy Independence and Security Act, this standard almost doubled. The 2007 RFS specifies minimum renewable-fuel production each calendar year from 2007 through 2022. It required 9b gal in 2008 and increases this level annually to 15.2b gal in 2012 and 36b gal in 2022. However, no more than 13.2b gal of corn ethanol could be used to satisfy the RFS in 2012, and no more than 15b gal of ethanol can be used for RFS compliance after 2015. The remainder of the RFS must be filled by so-called advanced biofuels, such as biodiesel from soybean oil and ethanol from cellulosic biomass. Under the expanded RFS, corn ethanol now comprises 10% of finished motor gasoline in the U.S., up from 3% in 2005. Not surprisingly, the period between 2005-2010 saw massive expansion of the corn for fuel demand. Considering the significant contributions that mandates played in the growth of corn fuel demand, there's no "right" answer to the effect of ethanol on demand elasticities—it's very circumstance dependent. For example, if production occurs only to satisfy the mandate, the elasticity would be zero. On the other hand, discretionary blending (use in excess of the mandate) and exports may be very elastic, especially in the long run. If gasoline is expensive enough and blend wall issues are resolved, the (long-run) price elasticity of ethanol demand would be almost infinite. That would mean supply side shocks would have big impacts on ethanol use, but no effect on long-run corn prices, which would presumably be determined by gasoline prices. On the other extreme, if oil prices are low and mandates are binding, the elasticity of ethanol demand with respect to corn prices would be almost zero. Even in the situation where long-run elasticities are infinite, short run elasticities will be limited by existing production capacity, etc.

Considering the insensitivity of mandates to the price of corn it is reasonable to assume that the growth of ethanol has probably reduced short-run corn demand price elasticity. However, the long-run effect is less clear, especially if you consider the possibility that the policies themselves may have been endogenous. Such question are outside the scope of this analysis. For this research the author simply highlights that much of the growth in corn consumption has occurred not due to changes in food or feed markets, and that the ethanol industry may have a very different set of drivers.   While corn used for the production of ethanol has represented a significant increase in the total consumption of corn, it must also be note that approximately 30% of the corn that was brought into ethanol production came out as a viable feed ingredient—Distillers Dry Grain (DDG).

To summarize, total domestic consumption comes primarily from three different subsectors, food use ($d_{i,t}^{d}$), feed and residual use ($d_{i,t}^{f}$), and industrial use ($d_{i,t}^{l}$). Under the assumption that each demand can be structured as a total general-equilibrium linear function of price, the corn demand equations are given by:

$$d_{i,t}^{d} = \beta_0^d + \beta_1^d(P_{i,t}) + \beta_2^d(I_{i,t}) + \beta_3^d(pop_{i,t}) \qquad \textit{Eq. 3.11}$$

$$d_{i,t}^{f} = \beta_0^f + \beta_1^f(P_{i,t}) \qquad \textit{Eq. 3.12}$$

$$d_{i,t}^{l} = \beta_0^l + \beta_1^l(P_{i,t}) \qquad \textit{Eq. 3.13}$$

$$D_{i,t} = d^d_{i,t} + d^f_{i,t} + d^l_{i,t} \quad \textit{Eq. 3.14}$$

$$D_{i,t} = \beta^d_0 + \beta^d_1(P_{i,t}) + \beta^d_2(I_{i,t}) + \beta^d_3(pop_{i,t}) + \beta^f_0 + \beta^f_1(P_{i,t}) + \beta^l_0 + \beta^l_1(P_{i,t}) \quad \textit{Eq. 3.15}$$

which can be reduced to

$$D_{i,t} = (\beta^d_0 + \beta^f_0 + \beta^l_0) + (\beta^d_1 + \beta^f_1 + \beta^l_1)(P_{i,t}) + \beta^d_2 ln(I_{i,t}) + \beta^d_3 ln(pop_{i,t}) \quad \textit{Eq. 3.16}$$

Thus, only the primary factors from each of the sub-categories will be calibrated as explanatory variables in the $D_{i,t}$ model. These factors include population, income, and real own-prices. As previously discussed and applied to the total area allocation equation, Equation 3.16 is assumed to be a total demand function [89]. This assumption implies that the measure of the responsiveness of quantity to price represents the "total" elasticity of demand. In essence the "total" elasticity is equal to the Marshallian elasticity obtained holding the price of other goods constant, ${\partial D_i}/{\partial P_i}$, plus a term reflecting the effect of induced cross-price changes and their effects on the demand for the good in question: $\frac{\partial D_i}{\partial P_i} = \frac{\partial D_i}{\partial P_i} + \frac{\partial P_j}{\partial P_i}\frac{\partial D_i}{\partial P_j}$.

The total domestic consumption per person function selected for this analysis is structured as:

$$\widehat{D}_{i,t} = \frac{D_{i,t}}{pop_{i,t}} = f\left(\widehat{D}_{i,t-1}, \frac{I_{i,t}}{pop_{i,t}}, P_{i,t}\right) = \beta_0 + \beta_1(\widehat{D}_{i,t-1}) + \beta_2\left(\frac{I_{i,t}}{pop_{i,t}}\right) + \beta_3(P_{i,t}) \quad \textit{Eq. 3.17}$$

where variables in Equations 3.17 are defined as:

1. $\widehat{D}_{i,t}$ is the domestic consumption per capita in country i at time t,

2. $pop_{i,t}$ represents the population level in country i at time t,

3. $\widehat{D}_{i,t-1}$ represents lagged domestic consumption per capita in country i at time t,

4. $I_{i,t}$ is the real GDP level in country i at time t,

5. $P_{i,t}$ is real local currency price of corn in country i at time t.

Equation 3.17 has been converted to a consumption per capita basis to preserve unit elasticity of consumption with respect to population. Due to the strong likelihood of omitted variable bias in attempts at linearly estimating the elasticities for Equation 3.17, this author decided to utilize elasticity estimates documented within the literature. Table 14 presents documented own-price elasticities found in the literature.

Table 14. Demand Elasticities within the Literature

	Own Short-Run	Own Long-Run	Cross Price Short-Run	Comment	Sources
United States					
	-0.20	-0.20	0	Own-price	Westcott and Norton (2012)
	-0.15	-0.15	0	Used for welfare calculation	Du, Hayes, and Baker (2008)
	-0.15	-0.15	0	Used for welfare calculation	Elobeid and Tokgoz (2008)
	-0.22	?	?	Price, Not Restricted	CARD model
	-0.18				**Mean**
Argentina					
	-0.34	?	?	Price, Not Restricted	CARD model
	-0.34				**Mean**
Brazil					
	-0.35	?	?	Price, Not Restricted	CARD model
	-0.35				**Mean**
Canada					
	-0.15	-0.15	0	Price, Not Restricted	Bahrenian et al. (1986)
	-0.22	?	?	Price, Not Restricted	CARD model
	-0.19				**Mean**
Philippines					
	-0.31	-0.31	-0.81	Price, Not Restricted	Cardenas et al. (2005)
	-0.31	**-0.31**	**-0.81**		**Mean**
South Africa					
	-0.19	?	?	Price, Not Restricted	CARD model
	-0.19				**Mean**

Note:

It is unclear how the CARD model elasticities are estimated or whether they were based on equations that incorporated cross-price effects or allowed short- and long-run effects to differ. Nevertheless, own-price elasticities documented by Westcott and Norton [116], Bahrenian, Devadoss, and Meyers [117], Cardenas, De Villa, and Decena [118], and Elobeid and Tokgoz [119] were estimated without the presence of cross-price elasticities. Furthermore, Du, Hayes, and Baker [120] and Elobeid and Tokgoz [119] assumed a total demand for own-price elasticities of -0.15 within their welfare evaluations of U.S. ethanol policy.

Considering that documented total own-price elasticities of demand ranged from -.15 to -.31, the author assumes the least elastic short-run elasticity estimate to calibrate Equation 3.17 to. This elasticity also preserves consistency with estimates used in other welfare evaluations [119-120]. While all long-run elasticities presented in Table 23 are assumed to be equal to the short-run elasticity, the author views this as overly restrictive and instead assumes all long-run elasticities to be 2x the short-run. Reasons the author views assuming a long-run demand elasticity which equals the short-run as being overly restrictive include: 1) current general-equilibrium total elasticity assumptions have already restricted the short-run elasticity into a very inelastic state, 2) demand for corn is long-run elastic when linked to energy markets, and corn ethanol is a small share of transportation fuels, 3) demand for non-fuel is short-run inelastic however improvements in feed conversion efficiencies and adjustments in feed rations can increase the flexibility of long-run consumption. The author recognizes that such an ad hoc assignment of the long-run elasticity subjects the estimation to possible specification error. For example within a total demand specification a priori expectations are that short- and long-run elasticities to be similar in countries where food demand (e.g., low income countries in Africa and Latin America) dominates, but the two could differ dramatically in countries where feed and ethanol uses dominate.

However, given the limited documentation of long-run elasticities within the literature reviewed as well as the empirical limitation experienced in attempts to estimate such relationships directly, the author accepts the potential bias and suggests inferential caution. Table 15 presents the selected elasticities.

Table 15. 2000-2010 Average Demand Elasticity Assumptions w.r.t World Price

Region	Elasticity	Short-Run	Long-Run	Literature Avg. Short-Run
United States	Real Price, LC/MT	-0.15	-0.30	-0.18
Canada	Real Price, LC/MT	-0.15	-0.30	-0.19
Brazil	Real Price, LC/MT	-0.15	-0.30	-0.35
Argentina	Real Price, LC/MT	-0.15	-0.30	-0.34
South Africa	Real Price, LC/MT	-0.15	-0.30	-0.19
Philippines	Real Price, LC/MT	-0.15	-0.30	-0.31
R.O.W.	Real Price, $/MT	-0.15	-0.30	

The elasticity assumptions listed above were chosen to remain consistent with what is documented in literature. Understanding that there is no single way to generate a linear coefficient which will impose a specific elasticity assumption, the author opted to select a linear coefficient which implied a 2000-2010 period average short-run elasticity of -0.15. To do this the author manually solved for each linear coefficient by selecting an own-price coefficient which made the 2000-2010 average point estimated elasticity equate to -0.15. While this does not imply a constant short-run elasticity of -0.15 in every year it does, however, ensure that all point elasticities are within the vicinity of -0.15. The author accepts this method as a sufficient method of calibration.

The next section covers the final concept of total demand to be structured into the partial equilibrium model. Ending stocks, unlike total consumption just presented, does not represent a commodity flow. Therefore, in the long run, the year-over-year change in ending stocks is assumed to be marginal. This characteristic implies that the structural behavior of the ending stocks model does not to contribute to the overall long run demand elasticity. Nevertheless, it does play an important role in the system's short run stability.

3.5.3 ENDING STOCK MODEL

Ending stocks is the final variable to be endogenized within the model as its characteristics warrant separation from the consumption equation, $D_{i,t}$. Corn production occurs once a year; therefore, corn production's year-to-year stock holding is an important component of total demand. Stock accumulations are normally associated with three basic motivations: precautionary, speculative, and transactional demand [101].

The transactional demand component is reflected in the level of market activity or a percent of total production and can be captured by current prices and/or current production. Speculative demand represents the reaction of inventory holders to expectations of future price movements. Precautionary demand represents the level of reserve or savings which participants usually carry.

Several models have been developed to capture these stock holdings including the basic accelerator model [121], flexible accelerator model [94, 122], and the modified flexible accelerator model [123]. The accelerator model, which is the simplest model, assumes that inventories vary directly and proportionately with output which means that ending stocks are a function of the corn price and corn production. While it is simple and easy to use, it is criticized because it does not allow firms to partially adjust their stock levels during a particular period of time, or allow for discrepancies due to factors such as expectations about price and/or market conditions.

Lovell [123] considered the possibility that agents may adjust inventories based on speculative motives and developed the modified flexible accelerator model. It was the first attempt to introduce the speculative reaction of inventory holders to future price movements. The inclusion of expected price and future production represents speculative motives of future price movements. The modified flexible accelerator model encompasses all the motives associated with grain inventory accumulation. Where transactional demand varies directly with output, speculative demand is reflected by adaptive expectations and precautionary demand is reflected in the level of the constant terms or intercept [124].

Ending stocks are specified to be a function of current corn price, production and beginning stocks to capture the speculative, transactional and precautionary stock holding components. The domestic ending stocks function selected for this analysis is defined as:

$$K_{i,t} = f(S_{i,t}, P_{i,t}) = \beta_0 + \beta_1 ln(S_{i,t}) + \beta_2 ln(P_{i,t}) \qquad \textit{Eq. 3.18}$$

Variables in Equation 3.18 are defined as:

1. $K_{i,t}$ is the level of stocks in country i at time t,
2. $S_{i,t}$ represents the level of supply ($K_{i,t-1} + Q_{i,t}$) in country i at time t,
3. $P_{i,t}$ is real local currency price of corn in country i at time t.

Recognizing that the ending stock equation is not as complicated by the omission of other market effects as was the case in the area and total consumption equations, reasonable parameter estimate for Equation 3.18 can be more easily obtained using ordinary least squares methods. The following tables present the estimated linear fits for each country.

Table 16. Ending Stock Parameter Estimates

United States

Variable	Coefficient	Standard Error	t Value	Pr > |t|
Intercept	21045	12108	1.74	0.10
Current Supply	0.15	0.04	4.02	0.00
Own-Price	-26144	6383.31	-4.10	0.00
R-Square = 0.6397				

Canada

Variable	Coefficient	Standard Error	t Value	Pr > |t|
Intercept	285.27	354.68	0.80	0.44
Current Supply	0.33	0.05	6.85	0.00
Own-Price	-2347.55	371.96	-6.31	0.00
R-Square = 0.8626				

Brazil

Variable	Coefficient	Standard Error	t Value	Pr > |t|
Intercept	-6402.12	4124.15	-1.55	0.16
Current Supply	0.31	0.08	4.05	0.00
Own-Price	-1650	0.00	-Infty	<.0001
Restrict	6677	3081.10	2.17	0.02*
R-Square = 0.6008				

Argentina

Variable	Coefficient	Standard Error	t Value	Pr > |t|
Intercept	-1046.18	728.95	-1.44	0.19
Current Supply	0.14	0.04	3.76	0.00
Own-Price	-320	0.00	-Infty	<.0001
Restrict	938.17	675.94	1.39	0.18*
R-Square = 0.3663				

South Africa

Variable	Coefficient	Standard Error	t Value	Pr > |t|
Intercept	-1783.68	1158.19	-1.54	0.16
Current Supply	0.46	0.09	5.21	0.00
Own-Price	-118	0.00	-Infty	<.0001
Restrict	0.00	0.00	0.00	0.00
R-Square = 0.6405				

Philippines

Variable	Coefficient	Standard Error	t Value	Pr > |t|
Intercept	-46.55	225.677	-0.21	0.839
Current Supply	0.15	0.02	7.63	<.0001
Own-Price	-5.77	2.53	-2.28	0.04
R-Square = 0.8164				

Rest of World

Variable	Coefficient	Standard Error	t Value	Pr > |t|
Intercept	-83663	43801	-1.91	0.1047
Current Supply	0.47	0.102	4.62	0.0036
Own-Price	-41400	0	-Infty	<.0001
Restrict	12719	5495.55	2.31	0.0013*
R-Square = 0.81				

Note: * indicates probability computed using beta distribution
Note: Only the model statistics for current supply, own-price, and the restriction are included

Despite the simplicity of Equation 3.18 each model was able to explain a significant amount of the variation within each region's ending stocks. Estimated parameters are all statistically different from zero. Brazil, Argentina, South Africa, and ROW did, however, encounter sign issues during unrestricted estimation. To correct for sign problems, this research assumed a -0.50 own-price elasticity and reran the estimation process as a restricted regression analysis. The author's only reason for choosing a -0.50 own-price elasticity was to ensure that a moderate degree of responsiveness existed within the stocks equation to help absorb short-run exogenous yield shocks. Table 17 lists the selected short-run elasticity estimates selected for the analysis.

Table 17. Ending Stock Elasticity Assumptions

Region	Elasticity
United States	-0.67
Canada	-1.73
Brazil	-0.50
Argentina	-0.50
South Africa	-0.50
Philippines	-0.77
R.O.W	-0.50

Note: Elasticity w.r.t. Real Domestic Price (Local Currency per Metric Ton).

Having now covered all the structural components of the partial-equilibrium corn model, the next section presents the closing identity followed by a presentation of the estimated impacts generated by the calibrated model.

3.5.4 MODEL CLOSURE

In general, for each region, prices determine domestic supply and demand levels. Within this model structure, each regional price is modeled as a function of world price using a price transmission equation. Since each region is linked to the international markets via net trade position changes in one region will impact the other regions. Having selected parametric representations of all the necessary components of supply and demand and confirmed their compliance with a priori expectations and/or accepted their general plausibility under given constraints, each structural component can now be linked according to a closing identity. Equations 3.19-3.22 represent the market clearing conditions.

Total Quantity Supply: $Q_{i,t}^{S} = Y_{i,t} * A_{i,t} + K_{i,t-1} = f(P_{i,t}^{S})$ *Eq. 3.19*

Total Quantity Demand: $Q_{j,t}^{D} = D_{j,t} + K_{j,t} + \text{NetExports}_{j,t} = f(P_{j,t}^{D})$ *Eq. 3.20*

Market Clearing Condition: $\sum_{i=1}^{7} Q_{i,t}^{S} = \sum_{j=1}^{7} Q_{j,t}^{D}$ *Eq. 3.21*

such that: $P_{i,t}^{S} = P_{j,t}^{D} = \boldsymbol{P}$ for all i, j, and t *Eq. 3.22*

where $P_{i,t}^{S}$ is the price the producer is willing to sell for, $P_{j,t}^{D}$ is the price the consumer is willing to pay, and $\boldsymbol{P}$ is the international market clearing pricing which balances trade between buyers and sellers.

3.6 RESULTS

Running the international corn model under the 'no biotech traits' scenario suggests that the impact that the productivity-enhancing biotech traits in corn on world price is significant. The author considers the no-biotech scenario as a deviation from the historical baseline. In the scenario, the yield and cost shocks are fully implemented from 1996 through 2010. The author reports on the 2010 impact as the summary indicator of the long-run impact. The scenario run shows that if GM corn were no longer used in global agriculture, the losses of the yield and production-enhancing capabilities of the technology would have resulted in world prices of corn increasing by over 8% by the year 2010.

This section first presents the simulated world impacts to corn price, supply, and demand from the yield impacts suggested by the damage abatement stochastic operational predictor estimated in chapter 2 followed by the regional level evaluations. Within Tables 21-28 ‘Biotech Adoption’ indicates the actual historical share of total corn area for each region that was planted with a biotech traited cultivar (the counterfactual assumes its value will be zero) with all other variable representing counterfactual impacts of removing the biotech induced yield and cost impacts. All counterfactual changes are calculated as counterfactual minus actual baseline, and each value is presented with its percentage change for additional perspective.

3.6.1 World

By 2010, approximately 25% of world corn area was planted with biotech traited seed. Table 18 presents the estimated counterfactual impacts removing each considered biotech adopting country’s yield and cost impacts.

Table 18. World Impact, Estimated Change from Baseline

	1996	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Biotech Adoption	1.0%	2.7%	6.1%	7.0%	6.0%	6.0%	7.8%	9.3%	11.4%	13.1%	14.5%	19.7%	20.6%	24.6%	24.6%
Price[1]	0.1	1.0	3.1	3.9	3.1	2.5	3.9	4.8	2.5	6.1	8.5	14.0	12.9	10.7	16.1
% Change	0.1%	1.1%	4.0%	5.4%	4.2%	3.2%	4.3%	5.0%	3.0%	7.7%	7.1%	8.5%	8.1%	7.6%	7.6%
Yield[2]	0.00	-0.02	-0.06	-0.07	-0.07	-0.07	-0.10	-0.11	-0.08	-0.14	-0.16	-0.22	-0.21	-0.22	-0.26
% Change	-0.1%	-0.5%	-1.3%	-1.7%	-1.6%	-1.6%	-2.2%	-2.4%	-1.7%	-2.8%	-3.3%	-4.4%	-4.2%	-4.2%	-5.1%
Area Harvested[3]	0.00	0.03	0.19	0.51	0.81	0.95	1.05	1.29	1.46	1.58	1.82	2.20	2.84	3.18	3.23
% Change	0.0%	0.0%	0.1%	0.4%	0.6%	0.7%	0.8%	0.9%	1.0%	1.1%	1.2%	1.4%	1.8%	2.0%	2.0%
Production[4]	-0.33	-2.66	-7.16	-8.03	-5.96	-5.35	-8.47	-9.46	-4.48	-12.11	-15.06	-24.13	-19.75	-17.81	-26.17
% Change	-0.1%	-0.5%	-1.2%	-1.3%	-1.0%	-0.9%	-1.4%	-1.5%	-0.6%	-1.7%	-2.1%	-3.0%	-2.5%	-2.2%	-3.2%
Consumption[4]	-0.15	-1.34	-4.25	-6.51	-6.64	-6.06	-7.16	-8.48	-6.71	-9.20	-12.41	-18.65	-20.07	-18.92	-22.31
% Change	0.0%	-0.2%	-0.7%	-1.1%	-1.1%	-1.0%	-1.1%	-1.3%	-1.0%	-1.3%	-1.7%	-2.4%	-2.6%	-2.3%	-2.6%

Note: [1]USD/MT; [2] MT/HA; [3]Mill HA; [4]MMT.

The estimated counterfactual global impacts of lost production efficiencies from the biotech areas would have effectively lowered world yield levels by approximately 5.1%. The impact of the reductions in global yields led to significantly higher world corn prices, which in turn, expanded the extensification of corn production bringing additional agricultural area into agricultural production and/or away from other food crops. The resulting impacts on consumption was indicated by less affordable food supplies and reduced consumption. Scenario results indicated that had it not been for the adoption of biotech traited corn, world prices would have been 7.6% higher by 2010. Scenario estimates that had world prices been 7.6% higher, global consumption would have had to be reduced by over 22.3 million metric tons or 2.6%. However, due to the inelastic demand assumptions, reductions in global consumption was limited implying that despite higher expenditures consumptions patterns were relatively unaffected. The ramifications of aggregate consumers' insensitivity to the price change resulted in an additional 3.23 million hectors of agricultural land brought into world corn production in 2010. The estimated net counterfactual effect in 2010 from biotech corn indicated that had it not been for biotech corn adoption, global corn production would have been approximately 26.17 million metric tons or 3.2% lower. This production impact is within range of previous studies. Brookes and Barfoot [65] estimated the additional production to be 28.29 million tons.

The cumulative impacts of removing the biotech induced yield and cost impacts implies that total consumption across the 1996-2010 crop marketing years would have been reduced by approximately 148.87 million metric tons. To make up for lost intensive gains from biotech adoption it was estimated that, by 2010, an additional 3.23 million hectares would have been brought into corn production. Finally, the net cumulative impact on corn production was estimated to be over 166.94 million metric tons. The cumulative impact reported in [65] estimated the additional production to be 159.4 million tons.

3.6.2 United States

The US was one of the first countries to adopt biotechnology in 1996. By 2010, 86% of the corn area planted was planted with a biotech traited seed variety. It is important to note that GM traits are generally classified as either Herbicide Tolerant (HT) or Insect Resistant (IR). While the biotech adoption induced yield-impacts developed in chapter 2 did not explicitly attribute the yield gains to either the HT or IR GM technologies there are, however, different cost impact assumptions between HT and IR traits.

Of the traited area, HT corn has been used commercially in the US since 1997, and in 2010 was planted on 70% of the total US maize crop. The main benefit from HT corn has been to reduce production costs. Brookes and Barfoot [65] reported that average profitability improved by $20/ha- $25/ha in most years, although between 2008 and 2010, this fell to a range of $12/ha-$16/ha, largely due to the significant increase in glyphosate prices relative to other herbicides [65].

Within the US IR corn can be further disaggregated into Corn Borer Resistant (IR-CB) and Root Worm Resistant (IR-WR). The main farm impact from both technologies has been increased average yields. IR-CB was first planted in the US in1996, and in 2010, seed containing IR-CB traits was planted on 63% of the total US corn crop. The net impacts on cost of production has been a small increase of between $1/ha and $9/ha (additional cost of the IR-CB seed being higher than the estimated average $45-$16/ha reduction in insecticide cost) [65]. In the last three years, however, with the rising cost of technology, the net impact on cost has been an increase of $8/ha to $16/ha [65]. IR-RW corn has been planted commercially in the US since 2003. In 2010, 53% of the total US crop contained an IR-RW corn trait. The expected net impact on average operational costs of production has been estimated at +$2/ha to +$12/ha [65]. Weighting the various technologies' cost assumptions by their respective area shares determined the national average cost impact data presented in Table 22.

Table 19 presents the estimated counterfactual impacts of removing the US aggregate cost and yield impacts attributed to the adoption of biotech corn.

Table 19. United States Impact, Estimated Change from Baseline

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Biotech Adoption	4.4%	11.9%	28.1%	32.9%	25.0%	26.0%	34.0%	40.0%	47.0%	52.0%	61.0%	73.0%	80.0%	85.0%	86.0%
Yield[1]	0.0	-0.1	-0.3	-0.3	-0.3	-0.3	-0.4	-0.4	-0.3	-0.5	-0.7	-0.8	-0.8	-0.8	-0.9
% Change	-0.1%	-1.1%	-3.1%	-4.0%	-3.2%	-3.1%	-4.7%	-4.7%	-2.7%	-5.8%	-7.5%	-8.3%	-8.7%	-7.3%	-9.4%
Cost[2]	0.6	0.1	0.5	0.8	1.4	3.0	3.5	3.4	5.6	9.8	7.2	14.5	13.5	7.5	2.4
% Change	0.2%	0.0%	0.2%	0.3%	0.4%	0.9%	1.1%	1.0%	1.7%	2.7%	1.8%	3.3%	2.5%	1.2%	0.4%
Net Returns[2]	-0.8	-0.5	4.7	6.5	4.0	-3.0	-8.5	-3.1	-3.5	1.2	-17.8	-23.1	-34.1	-10.0	-54.2
Area Harvested[3]	-3.0	-3.7	16.3	38.9	44.0	23.9	1.1	-7.6	-22.4	-4.6	-44.0	-86.0	-154.1	-157.4	-207.2
% Change	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	-0.1%	0.0%	-0.2%	-0.2%	-0.5%	-0.5%	-0.6%
Production[4]	-337	-2691	-7549	-9161	-7726	-7395	-10780	-12219	-8280	-16295	-20454	-28355	-28130	-25679	-31502
% Change	-0.1%	-1.2%	-3.0%	-3.8%	-3.1%	-3.1%	-4.7%	-4.8%	-2.8%	-5.8%	-7.6%	-8.6%	-9.2%	-7.7%	-10.0%
Consumption[4]	-40.9	-377.1	-1244	-1935	-1994	-1825	-2179	-2623	-2095	-2917	-4012	-6151	-6796	-6517	-7901
% Change	0.0%	-0.2%	-0.7%	-1.0%	-1.0%	-0.9%	-1.1%	-1.2%	-0.9%	-1.3%	-1.7%	-2.4%	-2.6%	-2.3%	-2.8%

Note: [1] MT/HA; [2]USD/HA; [3]1000 HA; [4]1000 MT.

The counterfactual estimate of the change in national average net returns ranged from -$7/ha in 1996 to -$54/ha in 2010, suggesting that despite the lower output prices brought on by increased productivity, US producers have and continue to capture significant value from the adoption of biotech traited cultivars. Comparable findings documented in the literature suggest the net impacts of biotech seeds on farm profitability has been +$24/ha to +$87/ha [65]. Considering impacts of lower output prices were not captured within their estimates, the values reported within Table 22 are within a-priori expectations.

The combined impacts of lower expected yields, higher production costs, and higher expected output prices resulted in only marginal changes in the counterfactual area harvested. Counterfactual expectations suggest that US area harvested would have actually decreased by 0.6% had biotech corn not been adopted. This suggests that the lower expected returns, due to increased cost and lower productivity, would have actually led some US producers to shift away from corn production despite higher expected corn prices. The combined impacts of lower yields and reduced area equated to significantly lower production estimates in the counterfactual scenario. Counterfactual estimates suggest that had it not been for biotech corn adoption, US corn production would have been almost 10% lower in 2010. This significant reduction in US supplies would have put significant strain on both domestic and international markets. Nevertheless, the author's inelastic demand assumptions led to just under a 2.8% reduction in US domestic corn consumption which resulted in most of the counterfactual impacts of lost US production being absorbed by significant reductions in US exports.

3.6.3 Canada

In Canada, HT corn was first planted commercially in 1999. In 2009, the proportion of total plantings accounted for by varieties containing a HT trait was 53%. As in the US, the main benefit has been to reduce costs and to improve profitability levels. Average annual production cost from adopting HT corn were reported to have been reduced by between $12/ha and $18/ha up to 2007, but fell from 2008 to under $10/ha ($7/ha in 2010) due mainly to the higher price increases for glyphosate relative to other herbicides [65]. IR-CB corn has also been grown commercially in Canada since 1996. In 2010 it accounted for 78% of the total Canadian corn crop of 1.2 million ha. The impact of GM IR-CB corn in Canada has been very similar to the impact in the US (similar yield and cost of production impacts) [65]. IR-RW cultivars were also planted commercially for the first time in 2004 in Canada. In 2010, the area planted to IR-RW varieties was 23% [65].

Table 20. Canada Impact, Estimated Change from Baseline

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Biotech Adoption	0.1%	6.0%	19.0%	33.0%	41.0%	46.0%	57.0%	63.0%	48.5%	64.9%	66.9%	73.5%	98.8%	90.0%	90.0%
Yield[1]	0.0	-0.1	-0.2	-0.3	-0.4	-0.4	-0.5	-0.6	-0.4	-0.4	-0.6	-0.6	-0.5	-0.7	-0.5
% Change	0.0%	-0.8%	-2.0%	-3.6%	-5.7%	-6.4%	-7.8%	-7.0%	-5.4%	-4.9%	-6.8%	-7.6%	-5.1%	-8.6%	-4.9%
Cost[2]	-0.1	-0.7	-0.9	-0.4	-0.1	0.4	0.7	1.2	-8.4	4.5	3.8	4.8	4.5	6.3	4.2
% Change	0.0%	-0.2%	-0.3%	-0.1%	0.0%	0.1%	0.2%	0.4%	-2.9%	1.4%	1.1%	1.2%	0.9%	1.2%	0.8%
Net Returns[2]	0.9	2.2	12.7	9.5	-7.7	-17.4	-25.3	-19.0	-8.5	12.3	-5.9	-0.7	32.7	-24.7	43.0
Area Harvested[3]	0.3	0.8	3.2	4.1	2.2	-1.3	-5.1	-7.5	-7.7	-4.1	-4.0	-3.3	1.6	-1.5	1.2
% Change	0.0%	0.1%	0.3%	0.4%	0.2%	-0.1%	-0.4%	-0.6%	-0.7%	-0.4%	-0.4%	-0.2%	0.1%	-0.1%	0.1%
Production[4]	1.8	-55.2	-156.9	-299.5	-375.4	-541.2	-732.6	-730.0	-537.3	-487.3	-644.1	-906.4	-527.0	-830.4	-564.5
% Change	0.0%	-0.8%	-1.8%	-3.3%	-5.5%	-6.5%	-8.1%	-7.6%	-6.1%	-5.2%	-7.2%	-7.8%	-5.0%	-8.7%	-4.8%
Consumption[4]	-2.0	-19.3	-71.3	-113.2	-116.9	-108.6	-129.8	-149.7	-115.1	-158.4	-205.1	-300.8	-298.5	-291.0	-330.6
% Change	0.0%	-0.2%	-0.8%	-1.3%	-1.2%	-0.9%	-1.0%	-1.3%	-1.1%	-1.5%	-1.8%	-2.2%	-2.6%	-2.5%	-2.9%

Note: [1] MT/HA; [2]USD/HA; [3]1000 HA; [4]1000 MT.

Like the US, Canada was an early adopter of biotechnology, with the technology now dominating production of corn. Based on cost savings, yield impacts, and adjusted world prices the counterfactual change in national average net returns was estimated to range between -$25/ha to $43/ha over the simulated period. Smaller cost reductions and lower yield impacts than what was experienced in the US resulted in Canadian net returns being more exposed to the counterfactually higher world corn prices. This is not to say Canadian producers were ever made worse off by adopting GM corn, assuming adoption would still have occurred in other countries. Had they not adopted, given current global adoption trends, counterfactual change in national average net returns would have been estimated to range between -$5/ha to -$114/ha throughout the simulated period. This implies that, had they not adopted biotech corn given the adoption levels of the rest of the world, the counterfactual reductions in yields would have significantly reduced the national average net returns. What this does indicate, however, is the general consequence of introducing a productivity enhancing technology into a market characterized by an inelastic demand.

Much like the US, the combined impacts of lower expected yields, higher production costs, and higher expected output prices resulted in only marginal changes in the counterfactual area harvested. Counterfactual expectations suggest that on average, the Canadian area harvested would have generally remained unchanged, with marginal reductions in periods, had biotech corn not been adopted. The combined impacts of lower yields and marginally reduced area equated to significantly lower production numbers in the counterfactual. Counterfactual estimates suggest that had it not been for biotech corn adoption, Canadian corn production would have been an average of 5.2% lower than what it was the 1996-2010 period. This significant reduction in Canadian supplies combined with the tightness in the global supplies would have put significant strain on domestic markets. Much like the situation in the US, the author's inelastic demand assumptions led to a 2.9% reduction in Canadian consumption by 2010. The counterfactual estimates suggest that had it not been for the biotech induced supply impact, Canadian corn stocks would have been significantly reduced by an average of 30% over the 1996-2010 crop marketing years.

3.6.4 Argentina

HT corn was first planted commercially in Argentina in 2004, and by 2010, 47% of the total corn area was planted to varieties containing a HT trait. During crop marketing years 2004-2006, biotech traits were only available as a single gene (not stacked with the IR trait) which resulted in limited adoption of HT technology in Argentina up to 2006 [65]. In 2007, stacked traits became available and contributed to the significant increase in the HT corn area in subsequent years. In 2010, stacked traited seed accounted for 85% of the total HT area. For HT traited seed, the cost of the technology (about $20/ha) has been broadly equal to the saving in herbicide costs, although since 2008, with the price increase of glyphosate relative to other herbicides, this became a net increase in costs of $2/ha-$5/ha [65]. IR varieties were commercially available earlier than HT varieties. IR varieties were first planted in 1998. In 2010, IR corn comprised 79% of the total Argentine corn crop. The main impact of using the technology on farm profitability has been via yield increases. No savings in costs of production have arisen for most farmers because very few corn growers in Argentina have traditionally used insecticides as a method of control for corn boring pests. As such, average costs of production increased by $20/ha-$22/ha (the cost of the technology) in years up to 2006[65]. From 2007, with stacked traited seed becoming available and widely used, the additional cost of the technology relative to conventional seed has increased to about $30/ha-$33/ha [65].

Table 21. Argentina Impact, Estimated Change from Baseline

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Biotech Adoption	0.0%	0.0%	0.4%	7.6%	18.8%	29.8%	46.1%	68.9%	86.8%	69.5%	80.2%	95.5%	83.6%	98.3%	86.0%
Yield[1]	0.0	0.0	0.0	-0.1	-0.1	-0.2	-0.3	-0.5	-0.4	-0.5	-0.3	-0.8	-0.6	-0.2	-0.8
% Change	0.0%	0.0%	-0.1%	-1.0%	-2.6%	-3.8%	-5.1%	-7.4%	-6.0%	-7.9%	-4.0%	-12.3%	-10.5%	-2.7%	-12.7%
Cost[2]	0.0	0.0	-0.1	-1.6	-4.2	-6.6	-10.3	-15.3	-11.0	-12.9	-12.2	-22.2	-23.7	-28.1	-25.5
% Change	0.0%	0.0%	0.0%	-0.9%	-2.3%	-3.6%	-5.8%	-8.9%	-6.0%	-5.9%	-5.0%	-8.5%	-8.0%	-8.9%	-7.5%
Net Returns[2]	0.5	6.3	16.4	18.6	10.3	3.4	4.4	-1.6	-7.6	8.8	39.6	-29.6	-8.1	84.7	-55.6
Area Harvested[3]	0.2	2.0	7.6	11.8	12.1	9.8	12.3	9.6	3.0	6.8	15.3	7.6	7.2	34.4	22.3
% Change	0.0%	0.1%	0.3%	0.4%	0.4%	0.4%	0.5%	0.4%	0.1%	0.3%	0.5%	0.2%	0.3%	1.3%	0.6%
Production[4]	1.1	12.0	33.2	-115.4	-331.8	-500.9	-711.8	-1053	-1203	-1209	-772.4	-2665	-1580	-338.1	-2737
% Change	0.0%	0.1%	0.2%	-0.7%	-2.2%	-3.4%	-4.6%	-7.0%	-5.9%	-7.7%	-3.4%	-12.1%	-10.2%	-1.5%	-12.2%
Consumption[4]	-0.6	-6.0	-20.8	-33.6	-33.2	-29.8	-49.0	-61.4	-51.8	-78.5	-107.1	-160.6	-168.8	-160.5	-205.1
% Change	0.0%	-0.1%	-0.3%	-0.6%	-0.6%	-0.7%	-1.2%	-1.4%	-1.0%	-1.3%	-1.6%	-2.4%	-2.6%	-2.3%	-2.9%

Note: [1] MT/HA; [2]USD/HA; [3]1000 HA; [4]1000 MT.

Like the US and Canada, Argentina was an early adopter. However, due to the combination of higher counterfactual world prices and lower counterfactual costs of production, the estimated counterfactual change in national average net returns was estimated to range between -$55/ha to +$84/ha throughout the simulated period. Nevertheless, in a separate running of the model where it was assumed that only Argentina not adopted, given current global adoption trends, the counterfactual change in national average net returns would have been estimated to range between -$0/ha to -$143/ha throughout the simulated period.

While most of the years prior to the introduction of the stacked traits were counterfactually estimated as net losses post 2006, a significant reversal occurred leading to significant gains being realized from the higher levels of productivity. It should be noted, however, that the 2006 and 2009 yield impacts were significantly lower due to good states of nature. Without the 2009 observation, the 2007-2010 average counterfactual net impact on farm profits is -$31/ha. Impacts reported in [65] over the same period report an estimated impact of -$3/ha to -$23/ha, suggesting that biotech adoption in recent years has significantly increased national average net returns.

Given that across all the single trait years, counterfactual returns were estimated to have been significantly larger, simulation indicates that on average, Argentine corn area would have increased slightly by 2% on average had biotech corn not been adopted. While increased area marginally offset the loss in production generated by the counterfactual loss in yield, the magnitude of the yield loss resulted in significantly lower production numbers in the counterfactual. Counterfactual estimates suggest that had it not been for biotech corn adoption, Argentine corn production would have been over 12.2% lower in 2010. Similar to conditions in the US, the significant reduction in Argentine supplies would have put significant strain on both domestic and international markets. Counterfactual reductions in domestic consumption were estimated to gradually increase from 0% in 1996 to 2.9% by 2010. With a majority of the Argentine corn crop being produced for the export market, most of the counterfactual impacts of lost Argentine production was absorbed by significant reductions in Argentine exports.

3.6.5 South Africa

South Africa was the first and remains the primary African country to embrace the technology, which was first commercially used in 2000. The technology was widely used in corn and now (in 2010) accounts for 78% of the country’s planted area.

HT corn has been grown commercially in South Africa since 2003, and in 2010, 36% of total corn plantings were herbicide tolerant. In the early years of adoption the cost saving from reduced expenditure on herbicides was slightly greater than the cost of the technology. However, in 2008 and 2009, farmers using the technology experienced a slight increase in the cost of production due to a significant rise in the global price of glyphosate relative to other herbicides. This was reported to have led to a negative net farm income balance of approximately -$2/ha [65]. In 2010, as the price for glyphosate has fallen relative to others, a marginal cost savings of $0.7/ha was realized by HT corn adopters [65].

IR corn has been grown commercially in South Africa since 2000. In 2010, 69% of the country's total corn crop used IR cultivars. The main impact has been an average yield improvement as the cost of the technology has been slightly larger than the average cost savings from no longer applying insecticides to control corn borer pests[65].

Table 22. South Africa Impact, Estimated Change from Baseline

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Biotech Adoption	0.0%	0.0%	0.0%	0.0%	4.0%	4.7%	6.5%	10.3%	24.0%	27.0%	44.0%	57.0%	62.0%	78.0%	78.0%
Yield[1]	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.3	-0.2	-0.3	-0.3
% Change	0.0%	0.0%	0.0%	0.0%	-0.2%	-0.5%	-0.6%	-0.8%	-1.8%	-2.6%	-5.9%	-7.4%	-4.6%	-7.3%	-6.9%
Cost[2]	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.3	-0.4	1.1	-2.8	-1.7	-1.3
% Change	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	-0.1%	0.2%	-0.6%	-0.3%	-0.2%
Net Returns[2]	0.3	2.2	6.9	11.6	7.2	6.0	8.9	11.7	3.6	12.9	2.6	2.2	24.3	0.5	2.3
Area Harvested[3]	0.3	2.5	9.8	17.9	21.5	22.4	32.9	37.6	31.0	31.5	31.9	21.6	34.5	22.3	19.9
% Change	0.0%	0.1%	0.3%	0.5%	0.7%	0.6%	0.9%	1.1%	1.0%	1.6%	1.1%	0.7%	1.2%	0.7%	0.7%
Production[4]	0.7	5.4	22.0	55.7	34.9	17.3	33.0	34.4	-94.9	-76.5	-358.5	-889.7	-436.7	-895.6	-684.9
% Change	0.0%	0.1%	0.3%	0.5%	0.4%	0.2%	0.3%	0.4%	-0.8%	-1.1%	-4.9%	-6.8%	-3.5%	-6.7%	-6.3%
Consumption[4]	-0.9	-8.7	-33.8	-56.9	-63.2	-80.6	-85.3	-89.2	-62.2	-110.9	-167.4	-270.7	-288.2	-274.9	-296.4
% Change	0.0%	-0.1%	-0.4%	-0.6%	-0.7%	-1.0%	-1.0%	-1.0%	-0.6%	-1.4%	-1.9%	-2.8%	-2.9%	-2.7%	-2.9%

Note: [1] MT/HA; [2]USD/HA; [3]1000 HA; [4]1000 MT.

While the adoption of GM corn resulted in significant gains in aggregate yield levels, the counterfactual world price impacts from the early adopters resulted in lower than expected gains in farm profitability. The counterfactual impacts of removing the effects of biotech corn adoption suggest that post adoption losses averaged $8/ha. Nevertheless if biotech had not been adopted given current world adoption levels, average counterfactual net returns are estimated to have been -$20/ha. The difference suggests that the adoption of biotech corn raised the national average net returns by approximately $20/ha. In 2010, this difference was estimated to have been $58/ha which is comparable to the 2010 net farm income gains of +$68/ha reported in [65].

As in other biotech adopting countries, the counterfactual impact on area harvested was estimated to marginally change in response to higher world prices. While area was estimated to have steadily increased in response to higher world prices through the 1996-2006 crop marketing years, the larger yield impacts induced by higher levels of national adoption post 2006 offset much of the counterfactual increases in area harvested. The combined effect of lower yield and only marginal increases in area resulted in a significant reduction in South African corn production by 2010. Table 25 indicated that had GM corn not been adopted national corn production would have been 6.3% lower in 2010. This impact is comparable with the 2010 national corn production impact of 7.3% reported in [65].

3.6.6 The Philippines

HT corn was first grown commercially in 2006, and in 2010 was planted on 20% of the Philippines total corn area. Based on the cost of implementing the GM-based biotechnology of $24-$27/ha, recent analysis by Gonsales et al. [125] suggested a net cost saving (reduced weed control costs from reduced cost of herbicides and less hand weeding) of $35/ha-$41/ha [65]. IR corn has been commercially planted in the Philippines since 2003. In 2010, 18% of corn area was planted with IR cultivars. Like Argentina, prior to the adoption of IR varieties, the use of chemical pest management was not well established. The lack of prior expenses led to a net cost increase from the adoption of IR seed varieties. The average annual insecticide cost savings of about $12/ha-$14/ha and average cost of the technology of $30/ha-$38/ha have been used. This resulted in a net increase in production cost of about $18-$24/ha [65].

Table 23. The Philippines Impact, Estimated Change from Baseline

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Biotech Adoption	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.2%	2.3%	2.9%	7.7%	9.0%	13.2%	19.4%	21.0%
Yield[1]	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1
% Change	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%	0.1%	0.0%	-0.1%	-0.5%	-1.3%	-1.6%	-2.3%	-2.5%
Cost[2]	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.2	-0.5	-0.6	-0.8	-0.4	-1.4	-1.6	0.4
% Change	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	-0.1%	-0.2%	-0.3%	-0.5%	-0.3%	-0.8%	-0.9%	0.2%
Net Returns[2]	0.2	1.5	5.5	6.7	5.6	4.7	7.6	9.9	5.6	14.3	19.7	31.4	27.8	19.3	28.4
Area Harvested[3]	0.3	3.6	14.3	24.4	29.2	31.6	36.3	42.2	40.9	59.2	66.0	74.1	84.7	81.3	76.2
% Change	0.0%	0.2%	0.5%	1.0%	1.2%	1.3%	1.5%	1.7%	1.7%	2.3%	2.5%	2.7%	3.2%	3.2%	2.9%
Production[4]	0.5	5.4	25.4	43.1	55.4	62.1	75.3	89.4	85.7	130.6	127.6	97.2	107.5	51.0	24.7
% Change	0.0%	0.2%	0.5%	1.0%	1.2%	1.4%	1.7%	1.8%	1.7%	2.2%	2.0%	1.3%	1.6%	0.8%	0.3%
Consumption[4]	-0.9	-8.7	-38.1	-60.3	-69.5	-66.5	-73.9	-85.1	-78.4	-109.7	-117.0	-139.7	-118.6	-106.8	-111.7
% Change	0.0%	-0.2%	-0.8%	-1.2%	-1.4%	-1.4%	-1.6%	-1.7%	-1.5%	-1.9%	-1.8%	-2.0%	-1.6%	-1.6%	-1.6%

Note: [1] MT/HA; [2]USD/HA; [3]1000 HA; [4]1000 MT.

In step with other late adopters, higher estimated world price led to significantly higher counterfactual net returns. Nevertheless, the difference between the counterfactual impacts presented in Table 26 and that which would have been expected assuming the Philippines had not realized the yield gains, given current global adoption levels, was estimated to average -$5/ha over the post adoption 2003-2010 crop marketing years. The difference in the impacts on net returns had increased significantly to -$18/ha by 2010 as biotech adoption had reached 21%.

Contrary to previous adopting countries, the counterfactual impact estimated for the Philippines suggest a slightly larger change in area harvested. Late and relatively lower adoption levels created a situation where the significant reductions in world prices brought on by adoption in other regions were significantly larger than the realized gains from adoption which led to relatively larger changes in the harvested area. The larger changes in the harvested area offset a significant share of the lost yield impact resulting in only a marginal counterfactual increase of 0.3% in the 2010 national production levels. Consumption was estimated to have been reduced by an average of 1.4% across the 1996-2010 estimation period.

3.6.7 Brazil

Brazil is the final biotech adopting region considered in this analysis. Brazil first adopted GM corn in 2008 when IR technology was the first to be introduced. IR corn has been commercially planted in Brazil since 2008. In 2010, 54% of the total crop was planted with IR varieties. Based on analysis from Galvao [85], the average cost of the technology was $22/ha in 2008 and $59 in 2009; insecticide cost savings were $42/ha in 2008 and $44/ha in 2009 making the net cost impact $20/ha in 2008 and -$15/ha in 2009. For the purposes of this analysis, 2009 impact and cost data were used for estimating impacts in 2010. 2010 was the first year in which HT corn was planted in Brazil and covered approximately 4% of the area planted to corn. Based on analysis by Galvao [85], the technology (seed premium) costs just over $17/ha but this was largely offset by a net saving in herbicide expenditure of about $14/ha [65].

Table 24. Brazil Impact, Estimated Change from Baseline

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Biotech Adoption	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	30.0%	53.0%	53.0%
Yield[1]	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.2	-0.3
% Change	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	-1.2%	-5.0%	-7.0%
Cost[2]	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	-5.7	-2.1
% Change	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.5%	-1.3%	-0.4%
Net Returns[2]	0.3	2.8	8.3	9.7	10.0	7.9	14.1	17.0	8.2	20.5	32.3	58.4	37.4	19.7	2.8
Area Harvested[3]	1.5	11.6	46.4	81.0	113.8	126.5	166.9	240.3	254.4	329.8	359.2	444.5	497.0	420.3	317.8
% Change	0.0%	0.1%	0.4%	0.6%	0.9%	1.1%	1.3%	1.9%	2.2%	2.6%	2.6%	3.0%	3.5%	3.3%	2.3%
Production[4]	3.9	30.7	124.1	208.8	387.8	429.8	670.1	923.0	880.7	1206	1466	1980	1181	-1047	-2772
% Change	0.0%	0.1%	0.4%	0.7%	0.9%	1.2%	1.5%	2.2%	2.5%	2.9%	2.9%	3.4%	2.3%	-1.9%	-4.8%
Consumption[4]	-4.1	-40.2	-147.6	-318.7	-345.2	-354.9	-495.1	-625.1	-488.3	-622.9	-755.2	-1029	-958.3	-890.9	-952.6
% Change	0.0%	-0.1%	-0.4%	-1.0%	-1.0%	-1.0%	-1.4%	-1.7%	-1.3%	-1.6%	-1.8%	-2.4%	-2.1%	-1.9%	-1.9%

Note: [1] MT/HA; [2]USD/HA; [3]1000 HA; [4]1000 MT.

Despite Brazil's late adoption of biotechnology, the significant yield gains and slight reduction in production cost abated much of the losses induced by global adoption levels. By 2007, the counterfactual change in national average net returns reached $58/ha before falling sharply to $3/ha in 2010. Re-running the scenario and assuming Brazil had not adopted current world adoption levels, the author finds that national average net returns would have been -$56/ha lower in 2010. Therefore, biotech adoption abated an expected $60/ha loss in national average net-returns which is near the 2008 and 2009 average improvement to farm income of $66/ha and $44/ha respectively reported in [65].

As with the Philippines, late adoption led to significant counterfactual increases in area harvested. The cumulative additional area that would have been brought into production was estimated to have been slightly over 3.4 million hectares. Until 2009, higher world prices stimulated significant increases in Brazilian corn production. However, the removal of significant yield impacts realized by the high levels of GM adoption in 2009-2010 left counterfactual production numbers significantly smaller. Counterfactual production in 2010 was estimated to have been 4.8% lower.

3.6.8 Rest of World

The Rest of World region represents the aggregate supply and utilization of all countries not identified in this analysis as being lead biotech adopting regions. While there are a few countries within the ROW aggregate that have significant adoption levels such as Portugal, Spain, and Uruguay, their overall contribution to the international markets is not large enough to warrant any special attention. Table 25 presents the counterfactual impacts of assuming biotechnology had not been adopted.

Table 25. Rest of World Impact, Estimated Change from Baseline

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Yield[1]	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
% Change	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.2%	0.1%	0.2%	0.2%	0.2%	0.2%	0.2%
Area Harvested[2]	0.0	10.4	96.8	334.0	588.2	733.8	809.4	970.6	1163	1159	1395	1739	2365	2786	3000
% Change	0.0%	0.0%	0.1%	0.4%	0.7%	0.8%	0.9%	1.1%	1.2%	1.2%	1.4%	1.7%	2.3%	2.7%	2.8%
Production[3]	0.0	35.1	342.1	1234	1996	2576	2979	3491	4672	4622	5573	6605	9633	10925	12062
% Change	0.0%	0.0%	0.1%	0.4%	0.8%	0.9%	1.0%	1.2%	1.4%	1.4%	1.6%	1.9%	2.4%	2.9%	3.0%
Consumption[3]	-83.7	-705.9	-2137	-3122	-4016	-3595	-4145	-4847	-3822	-5203	-7049	-10596	-11439	-10682	-12515
% Change	0.0%	-0.3%	-0.9%	-1.2%	-1.2%	-1.0%	-1.2%	-1.3%	-1.0%	-1.3%	-1.7%	-2.5%	-2.6%	-2.4%	-2.7%

Note: [1] MT/HA; [2]1000 HA; [3]1000 MT.

Table 28 indicates the endogenous influence of counterfactual increases in the world price of corn on ROW yields. ROW countries experienced a marginal increase in aggregate yield levels. Larger expected output prices in the counterfactual incentivized investments in other intensive technologies and practices. Area harvested is estimated to have increased significantly bringing in an additional 3 million hectare of land into corn production by 2010. The combination of a marginally higher yield and expanded area resulted in significant gains in ROW corn production. The large counterfactual reduction in US and Argentine corn exports put significant strain on the internationally tradable supplies. Consequently, ROW consumption was significantly reduced to satisfy the market clearing conditions.

Table 28 indicates that the adoption of biotech corn in the US, Canada, Argentina, South Africa, Philippines, and Brazil, significantly impacted ROW consumers and producers. Results suggest that had the productivity increases in adopting regions not been realized the ROW area would have resulted in an additional 3 million hectares brought into corn production by 2010. Furthermore, despite the expansion in area ROW consumers would have still had to reduce their total consumption by 2.7% to balance the total yield and cost impacts of biotech adoption.

3.6.9 SENSITIVITY ANALYSIS

While estimated results did correspond with impacts reported in other studies, uncertainty regarding the total supply and demand elasticities warrants a sensitivity assessment. To author manually scaled the base short and long-run elasticity assumption to reflect a more or less elastic total supply or demand response. Six alternative models were constructed representing six alternative levels of elasticity. The exogenous yield and cost impacts were then introduced into each model. Each of the six models then independently simulated six respective counterfactual supply, demand, and price impacts. Price impact are then compared to determine the general sensitivity of model results to elasticity assumptions. In total, there were six alternate scenarios. The impacts were computed with regional supply elasticities that were (a) double their original values and (b) half their original values. Likewise, impacts were computed with regional domestic demand elasticities that were (a) double their original values and (b) half their original values. The final two scenarios pertain strictly to the impact sensitivities to long-run elasticity assumptions. Wherein the impacts were computed with all regional long-run supply and consumptions elasticities being (a) equal the short-run elasticities and (b) assumed infinite (that is, lagged dependent variable coefficients were set equal to 1). Figure 14 presents the various counterfactual price impacts from the six different elasticity assumptions.

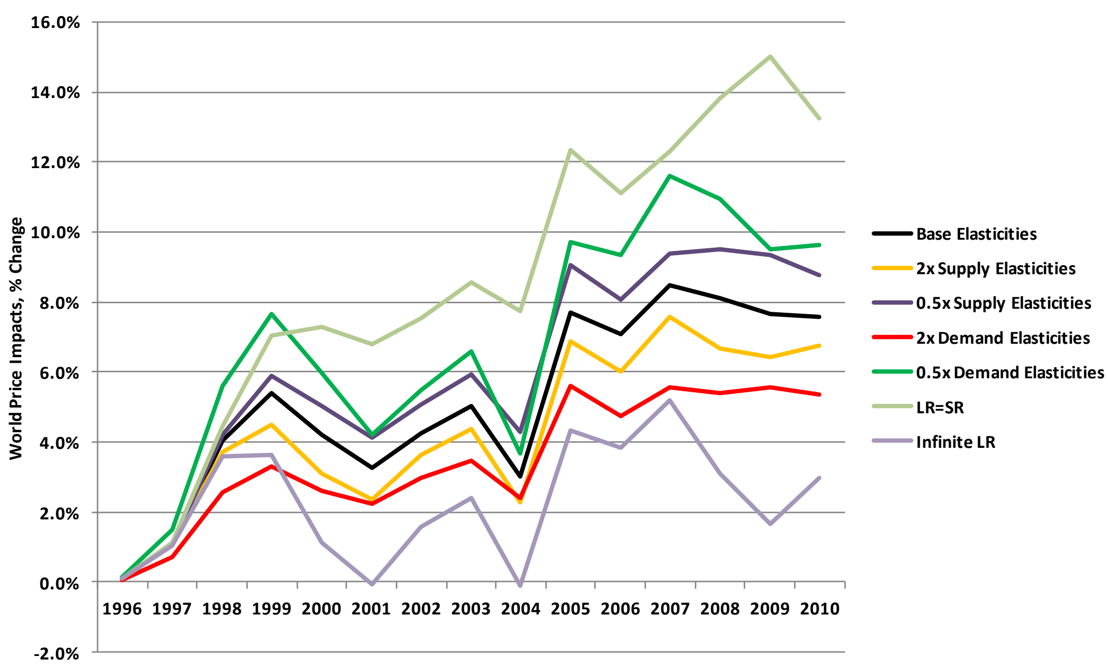

Figure 14. Sensitivity of the World Price Impacts to Elasticity Assumptions.

Sensitivity analysis presented in Figure 14 suggests that impacts are significantly more sensitive to variations in the demand elasticity assumption relative to the supply elasticity assumptions. Considering that the assumptions to double or halve the short-run demand elasticities resulted in simulated counterfactual impacts which neared the extreme cases where the long-run elasticities (given base supply and demand short-run elasticities) were either infinite or constrained to the short-run, it is suggested that the accuracy of the short-run elasticity assumptions are more critical than the long-run assumptions. If the world price impacts do in fact represent the upper bound it would imply that the counterfactual impacts on the national average net returns may represent the lower bound of the producer benefits, assuming accurate yield and cost impacts. The higher counterfactual world price impact would also imply, given the simplicity of the structural specification, that the counterfactual impacts on world area and consumption represent the upper bound of the likely impacts of not adopting biotech corn.

3.7 CONCLUSION

In this chapter the author has analyzed the international market impacts of GM corn in the United States, Canada, Argentina, South Africa, Philippines, Brazil and the ROW. Where the regulatory environment allowed for commercial use of GM corn, the rapid adoption of these technologies realized levels of 80-99% in all of the early adopting regions. GM corn has proven to significantly increase effective yield levels by increasing the production efficiencies of other production inputs and lowering the costs of production. This study evaluated the market impacts of biotech traits on international areas, production, consumption, trade, and world price in the global corn markets, through the use of a seven region single-market partial equilibrium corn model.

The estimated impact of the additional production as well and the impacts of the changes in production expenditures on markets and prices in the corn industry are significant. The modeling analysis of the potential impact of no longer using these traits in world agriculture shows that the world price of corn would have been 7.6% higher in 2010 than what actually occurred.

The effect of no longer using the current biotech traits in corn sector would also significantly impact both the supply and consumption of corn. Average global yields were estimated to fall by 5.1% by 2010. While it was estimated that there would have likely been some additional plantings induced by higher world prices it would have not, however, offset the yield impact effects of removing the impact of current adoption levels of biotech traits. The net effect would have been a net reduction in global production of 166.9 million metric tons cumulatively over the period from 1996-2010.. Furthermore, it was estimated that had it not been for the yield impacts of biotechnology, world consumption would have been reduced by more than 148.9 million metric tons due to higher world prices.

Up to this point, this dissertation has econometrically generated yield impacts from biotechnology adoption and stylized a partial equilibrium model that transformed the yield impacts into counterfactual estimates of world corn prices and international supply and demand situations. In the next chapter, welfare analysis will combine all of the information created above into cumulative ex post measures of consumer and producer welfare impacts from GM corn adoption.

CHAPTER 4. PRODUCER AND CONSUMER WELFARE: DISTRIBUTIONAL IMPACT 1996-2010

Abstract

Since first commercialized in 1996, biotech corn has experienced rapid adoption. By 2010 over 75% of the area planted in the United States, Canada, Argentina, Brazil, South Africa, and Philippines was planted with biotech seed. These countries represent a significant presence in the global corn markets—averaging 53% of world production and 83% of world exports from 1996-2010. The purpose of this research is to evaluate the ex post global economic efficiencies generated from the commercialization of biotech corn in these six countries. This study only focuses on the quantifiable market benefits accruing to producers and consumer stakeholders. As such, this analysis does not include the benefits to the input market or the value of non-pecuniary benefits. Global economic efficiencies are evaluated on: 1) the extent to which the adoption of biotech corn has impacted yields, and 2) the extent to which the adoption of biotech corn has impacted world production, price and distributional welfare. The extent to which biotech adoption has impacted corn is econometrically estimated via a model for technical inefficiency effects in a stochastic frontier production function for panel data. A partial equilibrium seven-region world model of the corn market calibrated to the 1996-2010 crop marketing years was developed to evaluate the ex post counterfactual world supply, demand and price impacts of biotech corn adoption. The cumulative 1996-2010 net global economic efficiencies realized from added biotech area was $38.9 billion. Of this total, the largest share went to U.S. consumers ($25.1 billion) followed by U.S. producers ($7.1 billion). The cumulative economic surplus gained by all consumers was estimated at $78 billion. The adoption of biotech corn has significantly increased production efficiencies of adopting producers which has led to larger and cheaper food supplies for all consumers.

4.1 INTRODUCTION

Growth in agricultural production is important for improved welfare and overall economic development. In developing regions, failure to achieve rapid growth in labor productivity within agricultural production can raise the cost of transferring labor and other resources from the agricultural to nonagricultural sector as development proceeds. Public and private agricultural research not only influences productivity, but when research is implemented it can become a major source of growth in agricultural production, income streams, and overall improvements in economic efficiencies.

The adoption of biotech crops, particularly herbicide-tolerant and Bt corn, has been rapid since their commercial introduction in 1996. For example, of the global hectarage of 158 million hectares of corn grown in 16 countries in 2010, over a quarter, 29% or 46.0 million hectares, were biotech corn [64]. Biotech corn has proven to offer producers distinct advantages over conventional varieties, such as higher yields through improved above- and below-ground pest control and lower pest control costs. Yet majorities of the world's corn producers remain unable to realize the benefits that these technologies have to offer, as regulatory barriers, lack of property rights, and/or capital constraints continue to limit grower choice.

In the previous two chapters, research demonstrated that use of biotech corn has significantly increased aggregate resource use efficiencies resulting in significantly higher yield levels for adopting regions. Results indicate that current (2010) adoption level in the United States, Canada, Argentina, Brazil, Philippines, and South Africa effectively increased the global aggregate yield level by over 5% and lowered world corn prices by almost 7%. In this chapter the author leverages both the predicted yield impacts covered in chapter 2 and the counterfactual international market impacts documented in chapter 3 to evaluate this dissertation's final hypothesis: Regulatory approval of biotech corn for commercial use has increased global economic welfare.

This study evaluates the long-run adoption impact to producer and consumer stakeholders in the United States, Canada, Argentina, Brazil, South Africa, the Philippines, and the rest of the world (ROW). Furthermore, this study focuses only on the quantifiable market benefits accruing to producer and consumer stakeholders from the adoption of biotech corn from 1996-2010. As such, this analysis does not include the benefits to the input market or the value of non-pecuniary benefits such as ease of pest management.

4.2 LITERATURE REVIEW

The success and controversy which has surrounded the commercial use of agricultural biotechnology has stimulated a wealth of literature relating to the farm and economic impacts of biotechnology adoption. Within the literature there have been empirical assessments of the welfare benefits of biotechnology adoption [12, 110, 126], [127], [128], [129-131], [5], [10]. However, only a few assess the impacts of biotech corn [132], [133], [134], and [135]. While these published assessments are regarded as significant contributions to the literature, there remains a substantial information gap regarding the global and temporal welfare impact. All existing literature on the welfare impacts of biotech corn have been evaluated within a single country closed economy context. Furthermore, the primary focus of the existing literature has been entirely on the producer welfare impacts. To date, there has been no assessment of the consumer welfare impacts of GM corn nor has there been an assessment of the distributional benefits at the multinational and global level. All existing literature, which addresses multinational welfare distribution, has primarily focused on the impacts from biotech cotton and soybeans. Furthermore, most studies were conducted during the earlier years of adoption. Thus, there is a major paucity for global distributional welfare assessment of biotech corn adoption. This chapter compiles empirical work from the previous two chapters to contribute the first ever global, multi-year, distributional welfare assessment of biotech corn adoption. Table 26 lists all of the published welfare assessments conducted on corn since first commercialized.

Table 26. Annual Producer and Social Welfare Impacts of Biotechnology

			Producer Welfare		Social Welfare	
	Source	Region	Farmers[1]	Technology Sellers[1]	Per Year[1]	Per Hectare[2]
Bt Corn						
	Brookes (2003a)	Spain	26.76		26.76	154.93
	Demont and Tollens (2004)	Spain	1.18	0.59	1.78	46.36
	Ostile et al. (1997)	US	43.92		43.92	17.8
	Benbrook (2001)	US	-18.4	131.6	113.2	-3.24
	Campenter and Gianessi (2001)	US	-6.1		-43.5	-6.1
	Trigo and Cap (2003)	Argentina	14.07	52.56	66.63	
	Scatasta, Wesseler and Demont (2005)	European Union			40.21	109.87
Ht Corn						
	Scatasta, Wesseler and Demont (2005)	European Union			69.24	113

Note: [1]million USD; [2]USD.

As illustrated by Table 26, there is limited empirical evidence on the impacts of biotech corn within the literature. Furthermore, there has been no consideration of the consumer impacts resulting from technology adoption. All welfare impacts presented were based on changes in revenue approach. The change in revenue model approximates changes in producer surplus directly from assumed changes in gross margins per acre at farm level. Changes are calculated by taking the difference between revenues and variable production costs from adoption, multiplied by the acreage, or extent of adoption. The impact of genetically engineered crops on revenues is investigated through impacts on yields. The impact on variable costs is investigated through impacts on costs for seed, technology, and crop protection.

The change in revenue method is by far the most straightforward and typically utilizes farm-level survey data on direct cost and yield impacts only. Limitations stem from the limited consideration of other economic factors such as assumptions on the industry supply or demand reactions. All other models are primarily stylized off a static partial equilibrium economic surplus model. However, the partial equilibrium surplus model is based on industry supply and demand functions (linear or non-linear) and assumes that agricultural innovations, such as transgenic crops act as a supply shifter. Open models are employed if trade between multiple regions is considered. Within the open model framework, technology spillovers are considered when an innovation developed in one region is allowed to affect production in foreign regions. Finally, the capturing of IPR within a welfare estimate has been the most recent addition to the welfare methods. Its inclusion is a direct consequence of the rent seeking behavior of a privately developed innovation relative to a publically developed innovation [111].

Alston, Norton, and Pardey [17] reviewed the criticisms of the economic surplus approach and considered alternatives to the partial-equilibrium economic surplus model. Their conclusion was that, for most purposes, the partial equilibrium economic surplus model is the best available method to evaluate returns to research [17]. Utilizing economic surplus concepts within a partial-equilibrium framework to measure the benefits and costs of research and technology adoption is the most common approach for analyzing the benefits or welfare effects. Nevertheless, there remains six types of criticism regarding the economic surplus as a welfare measure: 1) normativeness, 2) measurement error, 3) partial welfare analysis, 4) externalities and free riders, 5) transaction costs and incomplete risk markets, and 6) policy irrelevance [17]. While all contribute significantly to the merit of a welfare analysis, measurement error and partial welfare measures warrant discussion.

Within the welfare impact literature covering the benefits of biotechnology adoption, most welfare impacts are based on some form of partial measure or borrowed estimate and invoke strong assumptions regarding the shape of the supply and demand curves and the nature of the technology-induced supply shift. While various forms have been applied, none have proven to be without error. When estimating the benefits from agricultural research, measurement errors are inevitably introduced by assumptions about:

1. Functional forms for supply and demand
2. Elasticities of supply and demand
3. Other market parameters
4. The nature of the research-induced technical change and the corresponding shift in supply and demand

5. The size of the research-induced productivity improvement

6. The timing of the flows of the benefits and costs

Probably the most important error-prone assumption regards the nature of the technology-induced supply shift on the size and distribution of technology benefits. Given a linear supply function, total benefits from a parallel shift are almost *twice* the size of total benefits from a pivotal shift (of equal size at the pre-technology equilibrium). Unfortunately, economic theory is not informative about either the functional form of the supply and demand or the functional form (parallel, pivotal, proportional, or otherwise) of the technology-induced supply shift [17].

Alston et al. [17] explained that the reason for most of this uncertainty is in the use of the industry supply curve. The industry supply curve is based on the aggregation of supply curves for individual firms; thus, shifts in the industry curve depends on the effects of new technologies on the marginal costs of existing firms and on entry and exit of firms. In order to inform a selection, one would need to examine the characteristics of all individual firms' affected marginal costs as they relate to technology adoption in order to predict which types of firms would benefit from a particular new technology [66]. With limited availability of data necessary to properly address such questions, the formation of assumptions about the nature of the technology-induced supply shift are unavoidable.

The generally accepted approach in the absence of the information required to choose a particular type of shift is to employ a parallel shift [17]. Supportive of the parallel shift, Rose [136] argued that "For most innovations, the best information available may be a cost reduction estimate for a single point on the supply curve…[It] is unlikely that any knowledge of the shape of the supply, or the position at which the single estimate applies, will be available. The only realistic strategy is to assume that the supply shift is parallel." Additional support was also reasoned by Alston et al. [17] as they indicated that under the assumption of a parallel shift, the functional forms of the supply and demand are unimportant, and it is convenient to base the parallel shift off local linear approximations.

Alston, Sexton, and Zhang [137] later documented the effects of functional forms for supply and demand on the size and distribution of the economic returns from research conducted in a varying level of market competition. Using a combination of analytical results and numerical simulations, their findings suggest that when a parallel shift is assumed in a perfect competitive market, the combinations of the choice of functional forms for supply and demand is relatively unimportant for the estimation of research benefits.

The second most important aspect of the measurement issue relates to the sensitivity of a welfare measure to assumptions on supply-and-demand elasticities. Elasticity assumptions are much more important in relation to the distribution of benefit [138]. In particular, the more elastic supply is relative to demand, i.e., the greater the consumer share of total research benefit, and the smaller the producer share and vice versa. The potential impact of different choices for the value of demand and supply elasticities on social welfare impact estimates is investigated in [5] and [138].

Falck-Zepeda et al. [110] conducted a distributional comparison to assess the sensitivity to off-the-shelf selection of US soybean supply elasticity assumptions. Moschini et al. [5] and Price et al. [138] carried out the sensitivity analysis with respect to half and double the benchmark values chosen for demand and supply elasticities. Price et al. [138] concluded that the direction of overall global social welfare impact estimates does not change, but the size of its estimate does change considerably in some cases. Their findings indicated that changes in supply elasticities (especially for the U.S.) have dramatic effects on estimated total surplus gains. For example, the increase in estimated world welfare associated with Bt cotton adoption is 74% higher than in their base case when U.S. and ROW supply elasticities are cut in half. These conclusions about the role of elasticities, obtained using linear supply-and-demand functions with a parallel shift can be applied generally [17]. Table 27 represents the summary of corn welfare impact studies with assumed elasticity measures.

Table 27. Elasticity Assumptions

			Elasticity	
Source	**Year**	**Region**	**Demand**	**Supply**
Brookes (2003a)	2002	Spain	Infinite	0
Demont and Tollens (2004)	1998-2003	Spain	Infinite	2.5
Ostile et al. (1997)	1997	US	Infinite	0
Benbrook (2001)	1996-2001	US	Infinite	0
Campenter and Gianessi (2001)	1998-1999	US	Infinite	0
Trigo and Cap (2003)	1998-2003	Argentina	Infinite	0

Considering the uncertainties presented in chapter 3, regarding the sensitivity of market impact measures to assumed supply and demand elasticities, Table 30 has been included to illustrate all the documented elasticity assumptions used within the biotech corn welfare literature. The inclusion of Table 27 is not intended to criticize these studies nor their assumed elasticities. It must be understood that it was not the intent of these studies to assess the distributional or price impacts of technology adoption within these welfare studies. What the author wants to illustrate is that, despite several published global welfare impact assessments on soybean and cotton, there has never been a full welfare assessment on the impact of biotech corn.

The body of evidence presented throughout this dissertation has clearly shown a need for data in the form of an accessible model showing the value of biotech corn's effect on national productivity and consumer welfare. This research fills the gaps of existing welfare evaluation on GM corn adoption by contributing the following to literature on the welfare effect of biotech corn:

1. The first multi-national welfare assessment of biotech corn
2. The first distributional analysis of the welfare impacts of biotech corn
    a. Producer and consumer impacts
    b. Regional impacts
3. The first study to temporally assess the long-run distributional wealth effect of biotech corn adoption.
4. The first sensitivity analysis of assumed supply and demand elasticities of the corn industry.

While this research contributes much to the literature, it is not designed to determine the share of the value captured by technology suppliers. Moschini and Lapan [111] indicated that private innovators, endowed with the Intellectual Property Rights (IPR) provided by the legal system, will attempt to capture the benefits of their innovation through monopoly pricing. As a result of monopoly pricing, they concluded that the conventional welfare measures that apply to publically produced innovations will not be appropriate in these circumstances and in general will tend to overestimate the true gross benefits attributable to the innovations. Although this is an important conclusion, it should be noted that the most dramatic implication of correctly accounting for monopolistic behavior entailed by IPRs is not on the overall size of the benefits but on the distribution of the welfare gains from innovation. Nevertheless, within the [111] model, it is assumed that all producers used an identical production technology with decreasing returns to scale and constant elasticity of substitution. Falck-Zepeda, Trexler, and Nelson [12] indicated that under the identical producer assumption, the innovating monopolist prices the input at the producer's marginal value product, rather than at the marginal cost as expected under perfect competition. This implies that there is no change in the producer's cost of production and, therefore, no surplus can be passed on to the output market; thus, all changes in surplus are captured as monopoly profit. However, as indicated in chapter 2, the identical technology assumption does not hold in an empirical setting and is further complicated by lack of data to support the indirect profit function. Due to these conditions and understanding that the objective is in evaluating the producer and consumer welfare impacts, the author has not included any surplus estimate for the technology developer.

The author's strategy for estimating the surplus created by the introduction of GM corn by international producers and consumers is as follows: a) the technology-induced corn supply shift was estimated for each of the six GM corn adopting regions considered using data on yield, cost impacts, and net of increased seed cost; b) the impacts of the new technology on world and regional supply, demand, and price were calculated; c) Marshallian surplus distribution in domestic and international markets was estimated using the economic surplus approach as presented by Alston, Norton, and Pardey [17].

4.3 DATA AND METHOD

The author's model divides the world into seven regions: the United States, Canada, Argentina, Brazil, South Africa, Philippines, and the ROW. Such regional division allows the model to specifically describe individual economic characteristics of the main players in the corn market and to emphasize existing differences among them. The model shows how different regions are affected by the introduction of biotech corn and estimate their economic impact on each region separately [10].

The theoretical framework employed in this study measures the change in Marshallian surplus in the output market resulting from the adoption of biotech corn [138]. The analytical framework is characterized as a collection of large, open economies with varying rates of technology transfer. Considering the ex post nature of the analysis, historical biotechnology adoption rates reflect the rates of technology transfer.

The open economy model structure allows for trade between the biotech economies and the ROW and assumes that the biotech regions can significantly affect world prices through their exports. The framework postulates that commodity supply and demand functions can be modeled using linear equations [17], [138]. The total general-equilibrium supply and demand equations covered in Chapter 3 represent these linear supply and demand functions.

Fundamental to the calculation of economic welfare is the accuracy of the assumed technology-induced supply shift [17]. The size of the biotechnology-induced supply shift – the K-shift – is a crucial determinant of the total benefits from research. The accuracy of the estimate of K-shift will determine the accuracy and validity of the estimates of the benefits attributable to biotech adoption. As documented in chapters 2 and 3, biotechnology adoption has had both a yield impact and a cost impact; thus, in this analysis the K-shift is calculated as an additive impact.

$$K_{i,t} = \%\Delta Y_{i,t} + \%\Delta C_{i,t} \qquad \textit{Eq. 4.1}$$

where $\%\Delta Y_{i,t}$ is the percent change in aggregate yields and $\%\Delta C_{i,t}$ is the percent change in aggregate cost of production. Both measures are exogenously determined from the partial equilibrium model. In chapter 2, a stochastic frontier analysis was conducted in order to determine annual by country counterfactual yield impacts of biotechnology adoption. The derived efficiency gained from biotech adoption, measured by the reduction in distance between the frontier and observed production is attributable to adoption of biotechnology via damage abatement (as measured by the reduction in inefficiency). $\%\Delta C_{i,t}$ represents the remaining exogenous component of the K-shift.

As discussed in chapter 3, the use of GE crops triggers changes in several production expenses, particularly those related to seed technology, pesticide expenditures, labor and management requirements, and machinery operations as indicated in the literature review. Farmers pay for GE traits in the seeds that they plant in the form of a technology fee because GE seeds are considered proprietary. The market price of seed, which includes the technology fee, incorporates the costs associated with development, production, marketing, and distribution [139]. The price must be responsive to farmers' willingness to purchase the technology while ensuring a return on capital to the seed developers and their investors [4]. Nevertheless, studies have indicated that despite seed cost increases due to technology fees, increases in output and cost reductions through lower usage of other inputs have generally increased the farmers' gross margin [140].

Within a welfare framework, substantial changes in the cost of production as a result of biotechnology adoption impacts the supply curve (a parallel shift down is equivalent to a percentage change in production expense) and thus represents a welfare measure. The cost shift will be calculated based on data pulled from peer-reviewed literature and compiled by Brookes [65]. Following Equation 4.4 the resulting K-shift is presented in Table 28.

Table 28. Assumed Corn Supply-Shift (K-Shift) from Adoption of Biotechnology

	1996	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
United States	0.3%	1.2%	3.3%	4.2%	3.7%	4.1%	5.8%	5.8%	4.3%	8.3%	9.2%	11.5%	11.1%	8.3%	9.6%
Argentina	0.0%	0.0%	0.0%	0.2%	0.3%	0.3%	-0.6%	-1.4%	0.0%	1.9%	-1.2%	3.7%	2.2%	-6.4%	5.1%
Brazil	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.1%	4.1%	6.9%
Canada	0.0%	0.6%	1.7%	3.5%	5.6%	6.5%	8.0%	7.4%	2.4%	6.1%	7.7%	8.6%	5.9%	9.8%	5.7%
Philippines	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%	1.4%	1.1%	1.8%	3.1%
South Africa	0.0%	0.0%	0.0%	0.0%	0.3%	0.6%	0.8%	1.0%	2.0%	3.0%	6.0%	7.8%	4.2%	7.1%	6.7%

As indicated in Table 28, the largest biotechnology-induced supply shift occurs in the US followed by Canada. High yield impacts and a slight reduction in cost of production have resulted in larger estimated K-shifts. While Argentina did experience significant yield increases from the adoption of biotech corn, the significant increases in cost of production resulted in net losses in some years. However, it should be noted that the losses which appear in 2006 and 2009 are a result of the lower realized yield impact predicted given above average growing conditions; both independent and unknown prior to planting.

Having 1) defined and parameterized (by defining the parallel nature of supply and/or demand shifts and the elasticities), the situation of interest and 2) estimated the quantity and price effects from substituting the K-shift into the country-specific supply-and-demand equations of the calibrated partial equilibrium model (developed in chapter 3), the remaining step is to calculate the distributional welfare effect. While all regions in this model experience identical changes in equilibrium prices, changes in quantities supplied may vary regionally because of differences in rates of technology transfer, local supply-and-demand characteristics (as reflected in local elasticities of supply and demand) and the size of the localized shifts in supply and/or demand. The collection of all changes in quantities and price, along with the original information on the supply-and-demand shifts, provide sufficient information for the calculation of the full welfare consequences induced by the assumed equilibrium displacement.

Utilizing the collection of changes, the welfare impacts are estimated using the linear supply and demand schedules as well as the counterfactual shift in supply induced by the new technology [17]. The formulas for changes in producer surplus ($\Delta PS_{i,t}$), consumer surplus ($\Delta CS_{i,t}$) and net total surplus ($\Delta NTS_{i,t}$) in region i and year t are

$$\Delta PS_{i,t} = P_{w,t}^{0} Q_{i,t}^{0} (K_{i,t} - Z_{w,t})(1 + 0.5 Z_{w,t} \varepsilon_i) \qquad \textit{Eq. 4.2}$$

$$\Delta CS_{i,t} = P_{w,t}^{0} C_{i,t}^{0} Z_{w,t} (1 + 0.5 Z_{w,t} \eta_i) \qquad \textit{Eq. 4.3}$$

$$\Delta NTS_{i,t} = \Delta CS_{i,t} + \Delta PS_{i,t} \qquad \textit{Eq. 4.4}$$

$$Z_{w,t} = -\frac{P^*_{w,t} - P^0_{w,t}}{P^0_{w,t}} \qquad \textit{Eq. 4.5}$$

$$\eta_{it} = \left| \frac{\frac{C^*_{w,t} - C^0_{w,t}}{C^0_{w,t}}}{\frac{P^*_{w,t} - P^0_{w,t}}{P^0_{w,t}}} \right| \qquad \textit{Eq. 4.6}$$

$$\varepsilon_{it} = \left| \frac{\frac{Q^*_{w,t} - Q^0_{w,t}}{Q^0_{w,t}}}{\frac{P^*_{w,t} - P^0_{w,t}}{P^0_{w,t}}} \right| \qquad \textit{Eq. 4.7}$$

where $P^0_{w,t}$ is the baseline world corn price in year t, $Q^0_{i,t}$ and $C^0_{w,t}$ are baseline quantities produced and consumed respectively. $Z_{w,t}$ is the change in world market price due to introduction of the new technology. $P^*_{w,it}, Q^*_{w,it}$ and $C^*_{w,it}$ are the counterfactual estimates of world price, quantity produced, and quantity consumed respectively. $K_{i,t}$ is the vertical supply shift defined by Equation 4.1. η_{it} is the price elasticity of demand and ε_{it} is the price elasticity of supply calculated post convergence [112].

Then net total world surplus in any give year or cumulatively across the entire period are calculated, respectively as

$$\Delta NTS_{w,t} = \sum_{i=1}^{7} (\Delta CS_{i,t} + \Delta PS_{i,t}) \qquad \textit{Eq. 4.8}$$

$$\Delta NTS_{w} = \sum_{i=1}^{7} \sum_{t=1}^{11} (\Delta CS_{i,t} + \Delta PS_{i,t}) \qquad \textit{Eq. 4.9}$$

where $\Delta NTS_{w,t}$ is the net Global welfare for time t, and ΔNTS_w is the cumulative measure of global welfare gains to producers and consumers from biotechnology adoption.

4.4 RESULTS

The decision to plant GM crops has affected economic circumstances of not only the adopting farmers, but also the farmers who chose not to adopt them as production changes resulting from the widespread adoption of GE crops have influenced the prices received by farmers. As mentioned in the introduction, this study focuses only on the quantifiable market benefits accruing to producers and consumers. As such, this analysis does not include the value of all the non-pecuniary benefits and costs such as worker safety and greater flexibility in management, nor does it include the benefits accruing to the technology input market.

Leveraging the predicted yield impacts developed in chapter 2 and the market impact data generated in chapter 3, this section presents the distributed and net total welfare estimates for each region followed by the simulated sensitivity analysis of alternative supply and demand elasticities. Table 29 presents the change in consumer surplus in terms of real 2010 billion U.S. dollars.

Table 29. Consumer Surplus Change, Real 2010 Billion U.S. Dollars

	1996	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**Cumulative**
United States	0.03	0.26	0.77	0.98	0.77	0.63	0.95	1.21	0.64	1.58	2.14	3.91	3.44	3.09	4.65	25.05
Argentina	0.00	0.02	0.05	0.05	0.04	0.03	0.03	0.04	0.02	0.06	0.08	0.12	0.10	0.08	0.12	0.84
Brazil	0.01	0.08	0.22	0.26	0.20	0.16	0.23	0.25	0.13	0.30	0.42	0.70	0.65	0.53	0.80	4.96
Canada	0.00	0.01	0.04	0.04	0.04	0.04	0.06	0.06	0.03	0.07	0.10	0.20	0.16	0.13	0.19	1.17
Philippines	0.00	0.01	0.03	0.03	0.03	0.02	0.03	0.03	0.02	0.05	0.07	0.12	0.10	0.07	0.12	0.72
South Africa	0.00	0.02	0.05	0.06	0.04	0.03	0.05	0.06	0.03	0.07	0.10	0.17	0.15	0.12	0.17	1.10
ROW	0.06	0.51	1.47	1.86	1.44	1.17	1.79	2.21	1.17	2.89	4.08	6.74	6.04	5.02	7.69	44.13
World	0.10	0.90	2.62	3.29	2.56	2.07	3.14	3.85	2.04	5.02	6.98	11.96	10.64	9.05	13.74	77.97

Note: ROW = rest of the world.

As presented in Table 29, the counterfactual estimates indicate that by 2010 the consumer surplus increases resulting from the adoption of biotech corn reached $14 billion of which almost 56% went of ROW consumers and 34% went to US consumers. Significant increases in world supply and reduction in world price brought on by efficiency gains from the adoption of GM corn led to substantial gains in regional consumer surplus. US, Argentine, Brazilian, Canadian, Philippine, South African, and ROW consumers (including livestock producers, ethanol producers, shippers, brokers, and corn food consumers) are estimated to have received over $4.7, $0.1, $0.8, $0.2, $0.1, $0.2, and $7.7 billion in benefits respectively due to lower prices resulting from the adoption of biotech corn by 2010.

Considering that by 2010, only slightly over 25% of the world corn area had been planted to biotech corn, the continued regulation and capital constraints on commercial use in many ROW countries, while not directly evaluated in this analysis, are hypothesized to be contributing to significantly higher world prices based on the evidence presented in this and previous chapters.

Table 30. Producer Surplus Change, Real 2010 Billion U.S. Dollars

	1996	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**Cumulative**
United States	0.08	0.02	(0.20)	(0.27)	(0.13)	0.19	0.40	0.22	0.38	0.18	0.79	1.86	1.64	0.42	1.55	7.13
Argentina	(0.00)	(0.05)	(0.10)	(0.16)	(0.11)	(0.09)	(0.14)	(0.17)	(0.09)	(0.11)	(0.31)	(0.23)	(0.17)	(0.50)	(0.12)	(2.36)
Brazil	(0.01)	(0.07)	(0.21)	(0.25)	(0.25)	(0.16)	(0.30)	(0.30)	(0.13)	(0.33)	(0.54)	(0.98)	(0.57)	(0.33)	(0.13)	(4.54)
Canada	(0.00)	(0.00)	(0.02)	(0.02)	0.01	0.03	0.04	0.03	(0.00)	(0.01)	0.01	0.01	(0.04)	0.03	(0.05)	0.00
Philippines	(0.00)	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.05)	(0.06)	(0.10)	(0.09)	(0.06)	(0.08)	(0.62)
South Africa	(0.00)	(0.02)	(0.05)	(0.08)	(0.04)	(0.03)	(0.05)	(0.05)	(0.02)	(0.04)	(0.01)	(0.02)	(0.09)	(0.01)	(0.02)	(0.53)
ROW	(0.05)	(0.42)	(1.28)	(1.59)	(1.12)	(0.98)	(1.51)	(1.80)	(1.09)	(2.48)	(3.52)	(5.60)	(5.57)	(4.37)	(6.81)	(38.18)
World	0.01	(0.54)	(1.89)	(2.39)	(1.66)	(1.07)	(1.58)	(2.10)	(0.97)	(2.84)	(3.64)	(5.07)	(4.89)	(4.82)	(5.65)	(39.11)

Note: ROW = rest of the world.

Benefits received by corn producers ranged from -$6.8 to $1.6 billion by 2010. This range reflects the different assumptions concerning the extent of the technology's impacts on crop yields and pest control costs. Significant yield gains generated by early adoption and greater savings in pest control costs were the driving force behind the larger estimated US producer gains. US producers were estimated to have received an additional $1.6 billion in economic welfare due to the commercial adoption of biotech traited seed. It should be noted that estimates presented in Table 33 reflects the counterfactual changes in producer surplus had biotech not been commercialized in any part of the world (Note, signs in each table have been changed to reflect producer surplus gains given current level of international adoption.)

It should be noted that the figures presented in Table 30 do not reflect how each country's counterfactual benefits would have equated had only they not adopted given current international adoption levels. For example, in Brazil the estimated cumulative impact of producer surplus is estimated to have been -$3.92 billion which reflects the fact that: 1) Brazil did not adopt biotech corn until 2008, and 2) large increase in world corn supplies due to adoption in other regions led to significantly lower prices received by Brazilian farmers. Now, what the -$3.92 billion does not tell us is how much larger the loss would have been if Brazil would not have realized the significant productivity gains estimated in chapter 2. In order to determine this impact, the author re-estimates the counterfactual impacts for each country assuming that its respective adoption benefits had not been realized given current adoption levels. Results indicate that had Brazil not adopted biotech corn in 2008 and realized the productivity gains from adoption, then they would have lost an additional $1.25 billion. Therefore, estimates reflect what is commonly referred to as Cochran's Treadmill. A new technology is introduced which reduced costs and increases production efficiency, thus increasing corn supplies and eventually reduces market prices. Early adopters (US and Canada) sell increased production at lower cost which increases farm incomes but later drives down market returns. Late adopters realize the consequence of not adopting early through lowered farm incomes resulting from productivity depressed world prices due to early adopters. Late adopters eventually adopt the most efficient technologies to stay ahead of the declining real prices. Farm income distribution shifts to most efficient farms as less efficient farms shift to alternative crops. Largest winners are consumers as the treadmill continues to result in improved production efficiencies and lower food prices. Results for other late adopters including Argentina, South Africa and Philippines indicate that had these regions not adopted biotech corn given current world adoption levels of all other countries, then their respective additional losses would have been \$0.26, \$0.79, and \$0.1 billion. While Argentina was not necessarily a late adopter the lack of trait stacking until 2006 and increased cost of production undermined much of the benefits of early adoption despite significant yield gains.

While significant gains were realized by adopting regions, the 2010 world producer impacts resulted in a -\$5.65 billion loss in world producer surplus. Significant production efficiencies gained by biotech adopting region resulted in a -\$6.81 billion loss in ROW producer welfare due to lower world corn prices.

Table 31. Total Surplus Change, Real 2010 Billion U.S. Dollars

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Cumulative
United States	0.11	0.28	0.57	0.71	0.64	0.82	1.35	1.43	1.02	1.76	2.93	5.77	5.08	3.51	6.20	32.18
Argentina	(0.00)	(0.03)	(0.05)	(0.11)	(0.07)	(0.06)	(0.11)	(0.13)	(0.07)	(0.06)	(0.23)	(0.11)	(0.07)	(0.42)	(0.00)	(1.52)
Brazil	0.00	0.01	0.01	0.02	(0.04)	(0.01)	(0.07)	(0.05)	0.00	(0.02)	(0.11)	(0.28)	0.09	0.20	0.67	0.42
Canada	(0.00)	0.01	0.02	0.03	0.05	0.06	0.09	0.09	0.02	0.06	0.11	0.21	0.12	0.16	0.14	1.17
Philippines	0.00	0.00	(0.00)	0.00	0.00	0.00	0.00	(0.00)	(0.00)	(0.00)	0.00	0.01	0.02	0.02	0.04	0.10
South Africa	(0.00)	0.00	0.00	(0.02)	0.01	(0.00)	0.00	0.00	0.02	0.03	0.08	0.14	0.05	0.10	0.15	0.57
ROW	0.01	0.09	0.19	0.27	0.32	0.19	0.28	0.41	0.08	0.41	0.56	1.13	0.47	0.65	0.89	5.95
World	0.11	0.35	0.73	0.90	0.91	1.00	1.55	1.75	1.07	2.18	3.35	6.89	5.75	4.23	8.08	38.85

Note: ROW = rest of the world.

By 2010 the producer and consumer gain in net total world surplus from the adoption of biotech corn from years 1996-2010 was estimated at $8.08 billion with the US capturing $6.20 billion of the estimated benefit. Early adoption and reduced cost of production led to substantial gains for both producers and consumers. Argentina, on the other hand, did not fare as well as the other regions considered. While Argentine consumers did benefit significantly from higher yields, losses incurred by the growers because of lower prices and higher per-hectare production costs led to a net loss in total welfare given current global adoption levels. The fact that domestic consumption only represented on average 32% of total production meant that the value lost in the export market more than offset the cumulative consumer gains. Despite late adoption, Brazil was estimated to have had a $0.57 billion gain in total surplus. While late adoption led to several years where losses realized by farmers more than offset consumer gains, the significant gains realized by 2008-2010 adoption level led to a significant cumulative total surplus gain. Canada captured the second largest level of gains realized by the adopting regions. Even though Canada represents one of the smaller countries in terms of production and consumption, early adoption and minimal cost impacts allowed producers to stay ahead of declining real prices thus resulting in a cumulative increase in total surplus of $1.15 billion by 2010. The Philippines and South Africa both realized a cumulative gain in total surplus of $0.10 and $0.61 billion, respectively. While it is expected that the Philippines total gain was slightly underestimated due to lower than expected estimated yield impact, the gains that were estimated from the late low levels of adoption managed to offset additional losses to producers. South Africa, the first of the Sub-Saharan countries to commercially adopt GM corn, realized significant increases in welfare. High yield impacts and only marginal increases in production costs resulted in significant producer gains in years 2007-2010. Finally, ROW netted the second largest gain in total surplus estimated at $4.84 billion. Despite significant losses to ROW producers due to reduced world prices, the increases in affordability and total world supplies led to significant food security gains realized by ROW consumers (including direct human consumers, livestock producers, and industrial product producers).

While the estimates indicate that the commercialization of biotechnology in the United States, Canada, Argentina, Brazil, South Africa, and the Philippines has resulted in significant contributions to increasing global welfare, the author remains mindful of the data limitations and the uncertainty regarding assumptions used in chapters 2 and 3. Given the variability in the expected world price impacts as illustrated in the sensitivity analysis conducted in chapter 3, the next section extends the same scenarios into the welfare impacts to illustrate how such uncertainty regarding elasticity assumptions translates into variability in expected welfare impacts.

4.5 SENSITIVITY ANALYSIS

This section presents the sensitivity analysis regarding the supply elasticities. Similar to Price et al. [138] this section gauges the extent to which different supply and demand elasticities affect surplus estimates, and the elasticity values in the base scenarios were adjusted for each region. The benefits are computed for each region with supply elasticities that are (a) double their original values and (b) half their original values. Likewise, stakeholders' benefits are computed with demand elasticities that are (c) double their original values and (d) half their original values. Furthermore, to gauge sensitivity to long-run elasticities the author has computed the benefits assuming that the long-run elasticities were (e) infinite and (f) equal to the short-run.

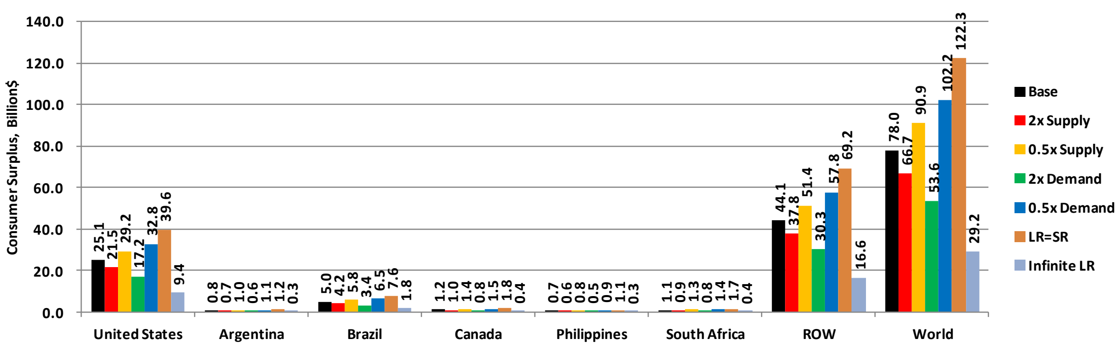

Figure 15. Sensitivity of Cumulative Consumer Surplus to Changes in Elasticity Assumptions, Real 2010 Billion U.S. Dollars.

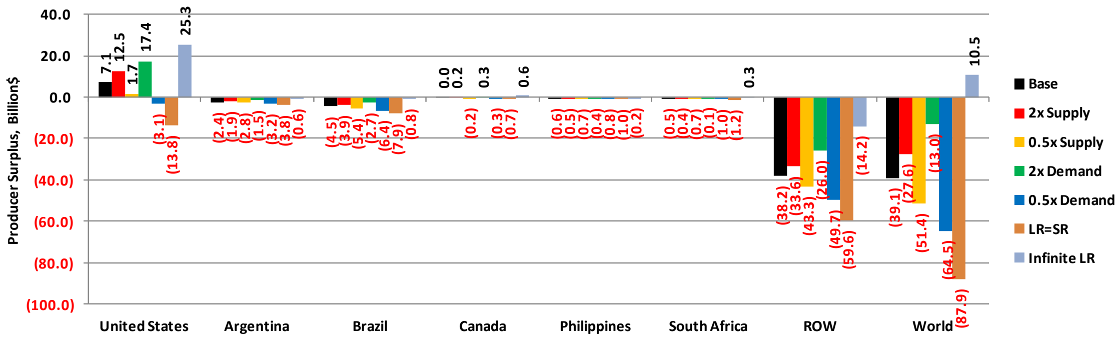

Figure 16. Sensitivity of Cumulative Producer Surplus to Changes in Elasticity Assumptions, Real 2010 Billion U.S. Dollars.

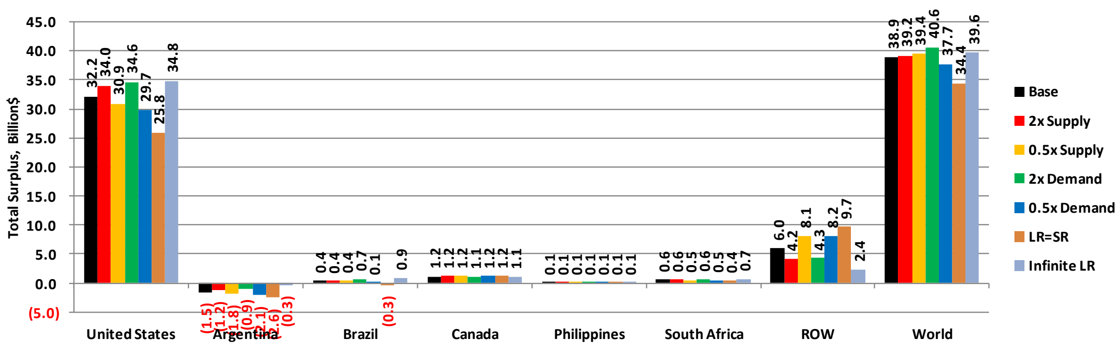

Figure 17. Sensitivity of Cumulative Total Surplus to Changes in Elasticity Assumptions, Real 2010 Billion U.S. Dollars.

The sensitivity analysis indicated that changes in the supply or demand elasticity only have a marginal effect on the estimated net total surplus gains (Figure 17). This is a significantly different conclusion than that indicated by Price et al. [138]. In their evaluation of cotton and soybeans, they found that total welfare was highly sensitive to changes in supply elasticity, reporting an increase in estimated world welfare associated with Bt cotton adoption as 74% higher than the base case when supply elasticities are cut in half. Furthermore, [138] indicated only modest sensitivity to changes in demand elasticity. In contrast to their findings, the sensitivity results documented in this analysis reflect the opposite levels of sensitivity. Net total surplus, illustrated in Figure 18, was insensitive to changes in supply or demand elasticity changes. The estimated increase in world welfare (net technology provider) associated with GM corn adoption only 2% higher than the base case when supply elasticities are cut in half. While [138] indicated more distributional sensitivity to supply elasticities relative to demand, this evaluation indicated that the distributional impacts of net total surplus between producers and consumers within the corn markets are more sensitive to demand rather than supply elasticities. As indicated in chapter 3, world prices are significantly less sensitive in the counterfactual to different assumptions regarding the supply elasticity relative to demand elasticity. Considering that in [138] soybeans welfare evaluation; (1) their long-run elasticities equaled their respective short-run elasticities, and (2) while their US demand was -0.5, their ROW initial long-run elasticity was -0.25, then by comparison their global long-run demand elasticity was less elastic then the one used here (-0.32 for US and approximately -0.32 for ROW). This observation limits the likelihood of the discrepancy being caused by a significantly less elastic long-run demand assumption. Reviewing their long-run supply elasticities (0.28 for US and 0.30 for ROW) indicates comparably the same story (0.46 for US and approximately 0.47 for ROW is the long-run supply elasticity here). A doubling or halving of the short-run elasticities in this analysis would lead to significantly larger potential variation in long-run supply response scenarios, yet the responses to larger and smaller elasticities did not reflect that found in [138]. Again, as with demand elasticities, this observation limits the likelihood of the discrepancy being caused by a relatively less elastic long-run demand assumption. The author suspects that an explanation as to why such differences have occurred can be found in this author's use of a calibrated net-return specification. The application of a net-return specification allows for producer to respond simultaneously to both changes in expected yields and changes in expected price. Considering that in the counterfactual, the losses in returns due to reductions in yields will be counter-balanced by increases in returns due to higher corn prices the author's a-priori expectations are that net impact to the counterfactual welfare evaluation should be less sensitive to changes in supply elasticities relative to demand. These findings indicate that previous sensitivity evaluations may have overestimated the sensitivity to supply elasticity uncertainty relative to demand. Findings in this evaluation indicate the uncertainty related to demand elasticity has a significantly larger impact on the distribution of net total economic surplus between producers and consumers than does the uncertainty in supply elasticity.

4.6 CONCLUSION AND FUTURE WORK

The estimated cumulative benefits arising from the adoption of biotech corn since it was first commercialized in 1996 varied significantly between regions. For each of the six biotech adopting regions, the estimated cumulative net welfare gains ranged from $32.2 billion to $-1.5 billion. These estimates of benefits from agricultural biotechnology are based on both the predicted yield impacts generated in chapter 2 and the estimated market impact of the predicted yield and assumed cost impacts generated in chapter 3. While there currently has not been any published welfare impacts for which to compare the estimated producer and consumer welfare, the author assumes all welfare measures are plausible based on the consistency of estimated yield and market impacts with their respective literature. Therefore, the author concludes that the commercialization of GM corn has significantly increased world total economic efficiencies. Empirical results suggest that the cumulative gains from the planting of biotech corn during the 1996-2010 time frame were $38.9 billion, representing 3.8% of the cumulative value of corn production for that time period. These estimates are the first of their kind within the literature.

The distribution of estimated net total benefits varied significantly across the seven regions. U.S. farmers received over 18% of the estimated total benefit from adopting biotech corn. Considering that the U.S. and Canadian growers have historically led the industry in terms of access and adoption of the latest technologies, results are supportive of Cochrane's treadmill and the effects of productivity enhancing technologies. Prior to the first commercialized biotech seed product, U.S. and Canadian growers arguably represented leaders of technology adoption in terms of access adoption and effective implementation of all pre-biotech era technologies. 1996 marked the start of a new era of seed technology. Both the U.S. and Canada developed strong functioning regulatory systems and IPR which stimulated quick adoption of new biotech events as they became commercialized. High levels of pre-biotech technology adoption followed by the comparatively higher efficiency of the U.S. and Canadian regulatory approval process, as measured by the number of commercialized trait packages and their successful adoption and use by growers has resulted in significant benefits to both growers and consumers. By 2010 there were 26 trait packages commercially approved and adopted in the U.S. and 10 commercially approved and adopted in Canada [64]. All other countries lagged significantly in their ability to generate regulatory approvals. This research supports the hypothesis that there is a strong positive relationship between the efficiency of a country's regulatory approval process and it growers' wealth. Furthermore, this research indicates that despite declining real world prices, grower returns post adoption continued to increase faster than the reduction in prices throughout 1996-2010 crop marketing years.

While declining real world prices continue to pressure regions which were slow to adopt or were only able to get 1-2 traits commercialized in the early years of the biotech era followed by significant increases in approvals later in the analysis, long-run impacts indicate that even in the later years of the evaluation, where the impacts on world prices were their largest, the accelerated commercial approval and adoption of biotech corn substantially increased grower returns and abated further losses from lower world prices. The two primary examples of this are found in South Africa and Brazil. Brazil in particular has experienced the most rapid turnarounds of all countries evaluated. Within three years, accelerated regulatory approvals resulted the commercial approval of 6 trait packages which were commercially adopted across 53% of Brazil's corn planted area resulting in a near complete reversal in the declining real grower income.

Estimates of biotech benefits are sensitive to a number of factors, including the analytical framework and supply elasticity assumptions. Sensitivity analysis indicates that changes in the demand elasticity assumptions have a more pronounced effect on the distribution of estimated benefits than do changes in the supply elasticity assumptions.

However, neither change in supply or demand elasticities significantly influenced the total cumulative welfare estimates, just the distribution of benefits between producers and consumers. Uncertainty related to supply elasticity assumptions was largely offset through the use of the net-returns specification within the area model. Allowing both price and yield to affect counterfactual supply response reduced the risk exposure related to uncertainty of supply elasticities. For example, doubling the supply elasticities increased the estimated total consumer and producer benefit by only 0.8% and caused U.S.'s corn producers' share of the estimated net total benefit to increase by 13% relative to the base case; whereas halving the demand elasticities reduced the estimated total benefit by 3% and caused U.S. corn producers' share of the estimated net total benefit to disappear.

Year-to-year variation in technology transfer affects the size and distribution of benefits across regions. Early adopters were estimated to have gained the most benefits across the estimation period. Despite continuous yield increases from continued increases in biotech corn adoption, early adopters continue to generate additional wealth streams from higher levels of adoption. Late adopters, while shown to have cumulative net losses, were able to offset lower world prices in later years as significant increases in production efficiencies allowed producers to realize higher yields, which offset the losses from lower prices. While significant benefits have been realized by technology adopting regions, the regions in which producers continue to be prevented from adoption have been estimated to have continuously growing losses. Cumulative impacts to the producer surplus for non-adopting region was estimated at $-38.2 billion.

Most welfare studies within the literature and mentioned within this evaluation analyzed the economic effects of GM varieties during the early period of their adoption (the latest study used data from 2001). Results of studies of adoption in agriculture, e.g., Feder et al. [141], suggest that early adopters of new yield increasing technologies gain early in the life of the technologies, but that their gains dissipate as prices go down. The U.S. was the dominant early adopter of GE varieties, yet long-run estimates show no sign of lower gains, as estimated gains for U.S. producers continue to increase despite world price impacts caused by increased production in other countries. Results indicate that despite the fact that most U.S. corn area is planted with traited seed, the continuous approval of various traits and trait stacks continue to keep U.S. producers ahead of the price curve unless, of course, the true demand elasticity is significantly less elastic, than has been assumed in this analysis, as shown earlier in Figure 9.

While efforts have been made to maximize the informational content generated in this analysis, the author acknowledges that by no means are the estimates presented in the following research to be viewed as irrefutable. The author recognizes that improvements can be made, and such improvements could lead to slightly different results. Restricted specification, limited data, and their statistical consequences have restricted he analysis to a lower level of accuracy. Nevertheless, the author views the merit in contributing to such an important topic should not be undermined by such limitations. Better information regarding yield and cost changes, as well as stronger priors for model parameter values would increase confidence in these surplus estimates. Uncertainty in these areas are the author's primary concerns, regarding accuracy and possible cause of measurement error. While the yield impacts predicted by the damage abatement model nested in a stochastic frontier production model did prove to generate plausible results, further research on ways to control for aggregate technology heterogeneity should improve the accuracy and robustness of the yield impact predictions. Cost impacts are another area which warrants further research. While the cost impacts for GM corn are far smaller than other GM crops, a better understanding of the national average impacts on corn production costs in Argentina, for example, could significantly impact the realized cumulative producer surplus estimate. Another area the author would like to see explored is the effects that the commercialization of biotechnology has had on the corn ethanol or livestock production. Given the significant world price impacts induced by the gains in corn production efficiencies there still remains many questions regarding long-run impacts in these areas. Finally, the author would like to see a general improvement in the information regarding short and long-run "total" general-equilibrium supply and demand elasticities. If partial welfare measures are to be reported, the author see this as an area in serious need of further research.

APPENDIX: LIST OF ABBREVIATIONS

CRS	Constant Returns to Scale
DDG	Distiller's Dry Grain
GM	Genetically Modified
HT	Herbicide Tolerant
HV	Hybrid Varieties
IR	Insect Resistant
IR-CB	Corn Borer Resistant
IR-WR	Root Worm Resistant
OPV	Open Pollinated Varieties
RFS	Renewable Fuels Standard
R&D	Research and Development

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