Zentrum für Entwicklungsforschung

Volatility of International Food Prices

Impacts on Resource Allocation and on Food Supply Response

Inaugural – Dissertation

Zur

Erlangung des Grades
Doktor der Agrarwissenschaften
(Dr.agr.)

der
Landwirtschaftlichen Fakultät

der
Rheinischen Friedrich-Wilhelms-Universität
Bonn

von
Mekbib Gebretsadik Haile

aus
Shoa, Äthiopien

Referent: Prof. Dr. Joachim von Braun

Korreferent: Prof. Dr. Thomas Heckelei

Tag der mündlichen Prüfung: 28 April 2015

Erscheinungsjahr: 2015

Volatility of International Food Prices: Impacts on Resource Allocation and on Food Supply Response

Abstract

Uncertainty is a quintessential feature of agricultural commodity prices. After about three decades of low and relatively stable price levels, we have experienced a dramatic rise and volatility in international food prices since 2005. Besides the traditional causes of price fluctuations, agricultural commodities are increasingly connected to energy and financial markets, with potentially destabilizing impacts on prices. The study focuses on the *global supply* response of the world's key staple crops, namely wheat, corn, soybeans, and rice, to changes in international food prices and volatility.

By applying the details of the crop calendar to derive monthly global acreage and production time series data for the period 1961–2010, we explicitly consider the role of seasonality in global agricultural supply response. Depending on the respective crop, the time series econometric results indicate that short-run elasticities are about 0.05 to 0.40; and price volatility tends to reduce acreage for most of the crops. Comparison of annual and monthly acreage response elasticities suggests that global acreage adjusts to new information and expectations seasonally. The analysis also indicates that acreage allocation is more sensitive to prices during spring than in winter, with varying responses across months. Furthermore, the study estimates global acreage, yield and production response of these key agricultural commodities by employing a multi–country, crop– and calendar–specific, seasonally disaggregated panel dataset, with price changes and price volatility applied accordingly. Besides confirming the time series econometric results, the dynamic panel supply response model results show that output price volatility has negative correlations with globally aggregated crop supply, implying that farmers shift land, other inputs, and yield-improving investments to crops with less volatile prices. In addition, we use the estimated coefficients to analyze whether the recent increase in prices and price volatility is an opportunity or a challenge for world food supply. Simulating the impact of the price dynamics since 2006, we find that price risk has reduced the production response of wheat in particular—and to a lesser extent, rice—thus dampening price incentive effects. The net-impact on production of the 2006–2010 price dynamics is an increase of about 3% for corn, 2% for soybeans, 1% for rice, and a decrease of about 1% for wheat. The study further develops country-specific acreage response models, which enable forecasting of planted acreages in large producer countries of major staple crops 2–3 months before planting.

Every supply response study requires some form of price expectation modelling, so do the supply response models of the present study. Using primary data from rural Ethiopia, we investigate price expectation formation of farmers. The empirical results show that information regarding current and past output prices in nearby markets, central wholesale prices and seasonal rainfall shape farmers' price expectations. Furthermore, the results indicate that farmers who invest in acquiring better price information are more likely to have smaller price prediction errors. This calls for public investments to provide smallholders with reliable market information.

Die Volatilität von internationalen Nahrungsmittelpreisen: Auswirkungen auf die Ressourcenallokation und das Nahrungsmittelangebot

Zusammenfassung

Unsicherheit ist eine wesentliche Eigenschaft von Agrarpreisen. Nach rund drei Jahrzehnten mit niedrigen und relativ stabilen Weltmarktpreisen, sind die Nahrungsmittelpreise seit 2005 stark gestiegen und volatil. Neben den traditionellen Ursachen von Preisschwankungen, kann die zunehmende Vernetzung von Agrarprodukten mit Energie- und Finanzmärkten möglicherweise einen destabilisierenden Einfluss auf Preise haben. Diese Studie untersucht die Anpassung des weltweiten Angebots von Grundnahrungsmitteln, wie Weizen, Mais, Soja und Reis, an die Veränderungen von internationalen Nahrungsmittelpreisen und deren Volatilität.

Dabei wird die Saisonabhängigkeit des globalen landwirtschaftlichen Angebots durch das Ableiten von Zeitreihendaten der monatlichen, globalen Anbaufläche und Produktion, für die Jahre 1961-2010, untersucht. Je nach Nutzpflanze zeigt die Zeitreihenanalyse kurzfristige Elastizitäten von 0,05 bis 0,40, während die Preisvolatilität die Anbaufläche für die meisten Pflanzen zu verringern scheint. Der Vergleich der jährlichen und monatlichen Anbauflächenelastizitäten zeigt, dass sich die weltweite Anbaufläche saisonal an neue Informationen und Erwartungen anpasst. Zudem schwankt die Allokation der Anbauflächen zwischen den Monaten und reagiert generell sensibler auf Preise während des Frühlings als im Winter. Desweitern schätzen wir die Reaktion der globalen Anbauflächen, des Ertrags und der Produktion der wichtigsten landwirtschaftlichen Güter. Dies geschieht anhand eines neu entwickelten internationalen, Pflanzen- und Kalender-spezifischen, saisonal desaggregierten Paneldatensatz, entsprechend den jeweiligen Preisänderungen und der Preisvolatilität. Die Ergebnisse des dynamischen Panelmodells der Angebotsreaktion bestätigen die Resultate der ökonometrischen Zeitreihenanalyse, und zeigen zudem, dass die Unbeständigkeit der landwirtschaftlichen Güterpreise negativ mit dem global aggregierten Angebot korreliert. Dies impliziert, dass Bauern Land, weitere Inputs und erntesteigernde Investitionen auf Anbaupflanzen mit geringerer Preisvolatilität konzentrieren. Die Koeffizienten der ökonometrischen Analyse zeigen, inwiefern Preissteigerungen und Preisschwankungen das weltweite Nahrungsmittelangebot beeinflussen. Durch die Simulation des Einflusses der Preisschwankungen seit 2006, konnten wir anhand der Weizenproduktion feststellen, dass das Preisrisiko einen durch die Preise generierten Produktionsanreiz dämpft. Der netto Einfluss der Preisschwankungen in den Jahren 2006-2010, führte zu einem Anstieg von 3% für Mais, 2% für Sojabohnen, 1% für Reis und einer Reduktion von rund 1% für Weizen. Diese Studie entwickelt des Weiteren ein länder-spezifisches Reaktionsmodel für Anbauflächen, welches diese in den größeren Produzentenländern, für die wichtigsten Grundnahrungsmittel und für einen Zeitraum von 2-3 Monaten vor der Aussaat, vorhersagt.

Eine Analyse der Angebotsanpassung benötigt komplementär immer auch ein Preiserwartungsmodel. Anhand von Primärdaten evaluieren wir daher die Preiserwartungen von Kleinbauern im ländlichen Äthiopien. Die empirischen Ergebnisse zeigen, dass Informationen über aktuelle und vergangene Preise auf nahen Getreidemärkten, zentrale Großhandelspreise und saisonale Niederschlagsmengen die Preiserwartung entscheidend formen. Zudem können Kleinbauern, die in die Beschaffung besserer Informationen investieren, die Preise nach einer Ernte besser antizipieren. Folglich wäre es sinnvoll Institutionen zu schaffen, die Marktinformationen als öffentliches Gut bereitstellen.

Table of Contents

List of Figures

List of Tables

Abbreviations

ADF	Augmented Dickey-Fuller
AMIS	Agricultural Market Information System
ARDL	Autoregressive Distributed Lag
ATA	Agricultural Transformation Agency
CONAB	Companhia Nacional de Abastecimento
CPI	Consumer Price Index
CSA	Central Statistical Agency
ECX	Ethiopian Commodity Exchange
EGTE	Ethiopian Grain Trade Enterprise
ERHS	Ethiopian Rural Household Survey
ERS	Economic Research Service
EU	European Union
FAO	Food and Agriculture Organization
FAPRI	Food and Agricultural Policy Research Institute
FAS	Foreign Agriculture Service
FE	Fixed Effects
GIEWS	Global Information and Early Warning System
GMM	Generalized Method of Moments
IFPRI	International Food Policy Research Institute
IHS	Inverse Hyperbolic Sine
IV	Instrument Variable
MNA	National Meteorology Agency
OCE	Office of the Chief Economist
OECD	Organization of Economic Co-operation and Development
OLS	Ordinary Least Squares
SIIA	Sistema Integrado de Información Agropecuaria
SSA	Sub-Saharan Africa
SUR	Seemingly Unrelated Regression
TLU	Tropical Livestock Unit
USDA	United States Department of Agriculture

Acknowledgements

Devoid the help of many people, it would have been very difficult if not impossible to finalize this thesis. My special thanks go to my supervisor Prof. Dr. Joachim von Braun for his continuous guidance and invaluable comments throughout the thesis work. He has given me several insightful feedbacks and suggestions that have greatly helped me to improve my thesis. I am highly indebted to Dr. Matthias Kalkuhl for the frequent discussions and comments throughout the writing of all of my thesis chapters. Anytime I went to his office, even at times he was really busy, I was welcome. I also gratefully acknowledge Prof. Dr. Thomas Heckelei for accepting to be my second supervisor and for his comments during the ZEF-IFPRI workshop and at other project meetings.

My sincere gratitude goes to the Federal Ministry for Economic Cooperation and Development (BMZ) and to Bayer CropScience AG for funding my PhD study through the 'Volatility in Commodity Markets, Trade Policy, and the Poor' research project. The support of Dr. Assefa Admassie and all other staff members of the Ethiopian Economic Association (EEA) is greatly acknowledged. They have made my field research much easier and more interesting. My appreciation goes to Dr. Maximo Torero, and other IFPRI colleagues, Dr. Carlos Martins-Filho, Dr. Miguel Robles, Dr. Manuel Hernandez, and others for their great comments and suggestions at several of our project meetings and workshops. I would also like to thank Dr. Getaw Tadesse for his guidance at the early stage of my PhD study, and for his review and suggestions on the earlier versions of chapters 2 and 5 of my thesis. I sincerely thank Dr. Andre Croppenstedt for his willingness to review some of my thesis chapters and for his great comments. I also thank Prof. Dr. Ulrich Hiemenz and Dr. Marc Müller for fruitful discussions at the early stage of my dissertation.

My sincere appreciation goes to Dr. Günther Manske, Dr. Guido Lüchters, Dr. Monika Kesting, Mr. Volker Merx, Mrs. Rosemary Zabel, Mrs. Maike Retat-Amin, and to all friends and colleagues at ZEF, especially to my 2011 batch mates, without whom my research and my stay at ZEF would not be as pleasant as it has been. I also acknowledge all the PhD students, research and student assistants in the 'volatility' project for several helpful discussions and research assistance.

My greatest gratitude goes to my wife, Asegedech Getachew, and my son, Elnathan, as well as to my parents and siblings, who have been a great moral support and inspiration in my entire life.

1. Introduction

1.1. The international food price dynamics

After about three decades of low and relatively stable level, international agricultural commodity prices experienced a dramatic rise since 2005 until they surge as large as an all all-time high level in June 2008 (in nominal terms). There was a short-lived price decline since the summer of 2008 until we have come across to a new food price increase that started in August 2010. The World Bank's Food Price Index, for example, rose by about 50 percent from June 2010 to February 2011 and attained its 2008 hike. Furthermore, agricultural commodity prices are predicted to increase, at least to remain high, in the short to medium run (FAO et al., 2011). Whether such a price increase outweighs the adverse impact of the accompanying price volatility and serves as an incentive for increasing agricultural production is the focus of this dissertation.

Several studies addressed potential causes (e.g. von Braun & Torero, 2009) and consequences (e.g. Ivanic & Martin, 2008) of high and volatile food prices. Categorizing the drivers of the global food prices as root, intermediate, and immediate causes, von Braun and Tadesse (2012) indicated that climate change, biofuel production, and excessive speculation in commodity futures are the most important root causes of observed price volatility. Kornher and Kalkuhl (2013) also found out that stocks, production shocks, and international price volatility are key determinants of domestic price variability in several developing countries. The food price volatility that we experienced since 2007/08 is characterized by long and extended spikes, sometimes called low frequency volatility. Such volatility has implications for resource allocation, investment decisions of farmers and thus on their future livelihoods. Even though there has been a great concern about the impacts of high food commodity prices on the poor, the evidence on the actual impacts of high and volatile food prices on poor households and smallholder farmers is scanty (Ivanic & Martin, 2008).

Not all price variations are troublesome, however. If prices change along a smooth trend or exhibit a regular cyclical or seasonal pattern, economic agents can anticipate them and make necessary ex-ante adjustments in their economic decisions. Price variations that reflect underlying market fundamentals are important because they contain useful public information on which economic agents base their economic decisions. However, variations in prices become costly for economic agents when they are abrupt and at excessive levels. Such price dynamics are problematic since they create uncertainty that introduces risk for economic agents, which could be producers, consumers, traders or the government. These are price variations that do not necessarily reflect market fundamentals and they can lead to suboptimal economic decisions. In other words, price volatility is problematic since it induces risk averse economic agents to make inefficient investment decisions.

von Braun and Tadesse (2012) provide a detailed description of different varieties of price dynamics and their potentially differential impacts on economic agents. Figure 1.1 reproduces the two variants of price changes, price trend and price volatility, for wheat, corn, soybeans, and rice since the 1980s. Price trend (depicted by the red lines in Figure 1.1) is the nominal price level after the cyclical component is removed using the Hodrick-Prescott filter. A price trend is an indicator of the long-term general tendency of average prices for a given period of time. For a given input and production cost, an upward price trend implies larger agricultural profits for producers, which could be invested in improving agricultural productivity. Price volatility (depicted by the dotted lines in Figure 1.1) is annualized variability of prices measured by the standard deviation of the logarithmic monthly prices in each year. It measures dispersion of a price series from the mean. Contrary to a price trend, price volatility introduces output price-risk, which has detrimental implications for producers' resource allocation and investment decisions (Moschini & Hennessy, 2001; Sandmo, 1971). The impact of price risk on smallholder producers has been extensively studied (Binswanger & Rosenzweig, 1986).

Changes in price level and volatility may follow different paths and may be driven by distinct underlying factors. While sustained changes in the market fundamentals (an increase in demand or reduction in supply) result in an upward price trend, shocks from both the supply and demand side of the market, market manipulations, and low stock levels may cause volatility. Although there is a general feeling that an increase in price level increases volatility, the relationship between them is not well defined. What is certain, however, is that the high prices of 2007/08 and 2011 have been associated with high price volatility (Gilbert & Morgan, 2010).

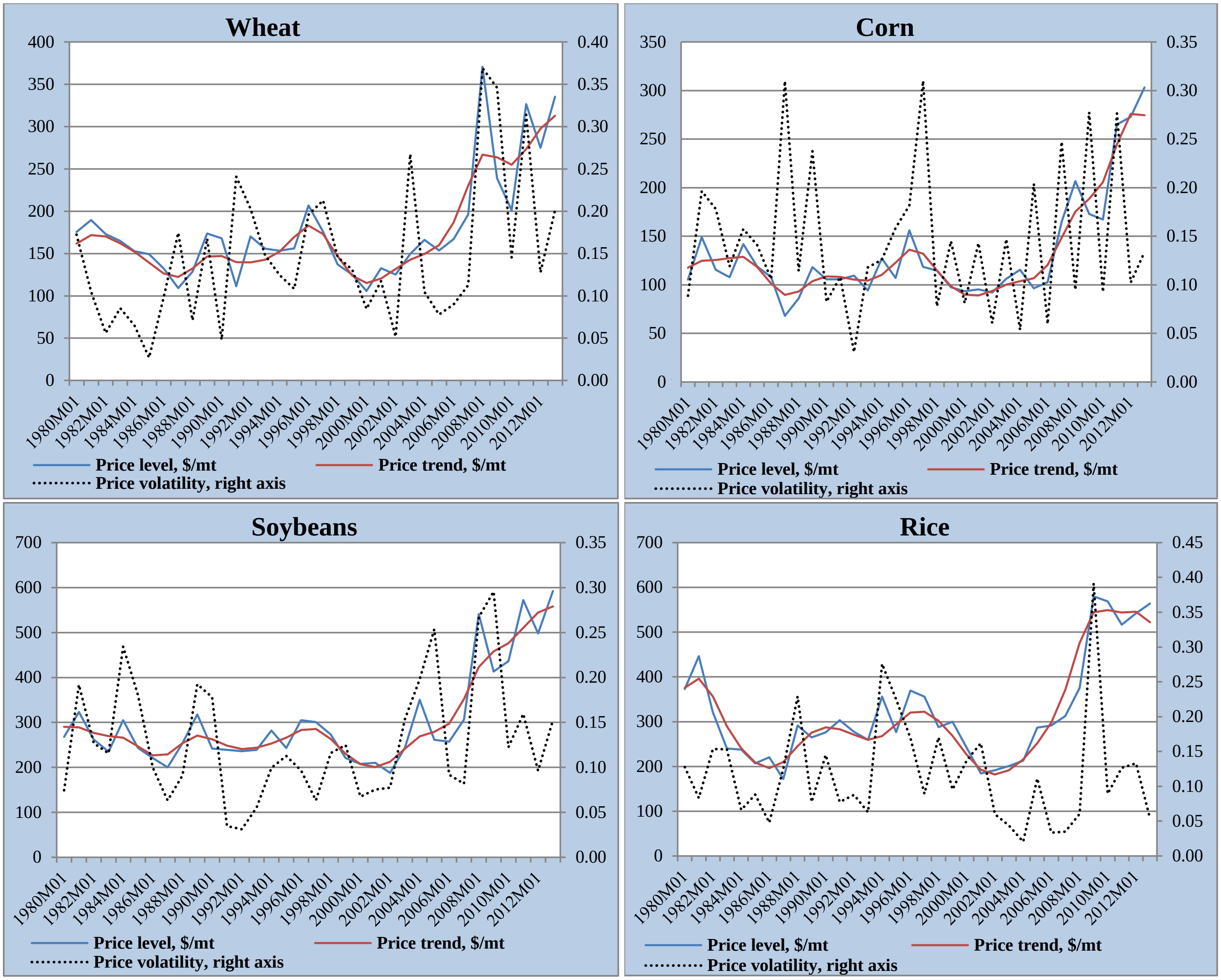

Figure 1.1. Global agricultural price dynamics for key staple commodities

Source: Adapted from von Braun and Tadesse (2012) using data from the World Bank (2014)

To this end, Figure 1.1 shows that all the level, trend and volatility of the selected agricultural commodity prices have dramatically increased since about 2005. Corn price, however, seems to exhibit large volatility in the 1980s and 1990s as well. While the upward price trend is typically expected to bring about a supply response in which producers allocate more land and other inputs to the agricultural sector and increase investment to improve yield growth (OECD, 2008), the volatility, on the other hand, might result in a distressed state of agriculture (Persson, 1999).

1.2. The global food supply dynamics

Currently, the factors behind high agricultural commodity prices are heatedly debated. Demand shocks that have persisted over the past decade played a significant role: the rapid worldwide shift towards corn use for fuel, aggressive Chinese soybean import, and higher demand for food (especially meat) due to higher income levels in several emerging economies are some of these demand-side causes (Abbott et al., 2011; Gilbert, 2010; Mitchell, 2008). These surges in demand, accompanied by the growing world population, have a remarkable bearing on the global food production and land allocation. For instance, the additional Chinese soybean demand was to a large extent met by soybean acreage expansion in Latin America (Abbott et al., 2011). There have also been several other acreage allocation and reallocation changes all over the world following the recent output price variations. While new acres are still important sources of changes in acreage for the developing and emerging countries, shifting land from low- to high-demand crops is also a key source in the developed countries where total arable land has become more binding. As a result, there have recently been remarkable foreign agricultural investments in many developing countries, primarily focusing on growing high-demand crops including corn, soybeans, wheat, rice, and many other biofuel crops (von Braun & Meinzen-Dick, 2009).

Moreover, such increases in demand for particular commodities also induce technological changes that enable improvements in productivity. Consequently, either as a result of changes in acreage allocation or yield enhancements in different parts of the globe, the world production share of countries in the southern and northern hemisphere has changed substantially over the past few decades. In general, there is a trend of shifting production of several key commodities, in particular soybeans, from North to South. This will have implications for trade patterns as well as international price volatility (Glauber & Miranda, 2014).

Wheat, corn, soybeans, and rice, which are the focus crops of this thesis, play a crucial global importance from both the demand and the supply side perspective. They are principal sources of food in several parts of the world with differential preferences across countries. To this end, Roberts and Schlenker (2009) reported that these crops comprise a three-quarter of the global calories content. The use of corn, soybeans and wheat as a feed for livestock and dairy purposes has also grown due to higher demand for meat following rapid economic growth in the emerging economies. Corn production has also another source of demand from the emerging market for biofuel. These crops also constitute a sizable share of global area and production. Corn, wheat and rice, respectively, are the three largest cereal crops cultivated around the world. According to data from FAO (2012), they constitute above 75% and 85% of global cereal area and production in 2010, respectively. About a third of both the global area and production of total oil crops is also attributed to soybeans.

Figure 1.2 depicts the annual global planted acreage of the four crops since 1960s. During the past 50 years, global production, acreage, and yield have increased, to different degrees, for all four key staple crops.

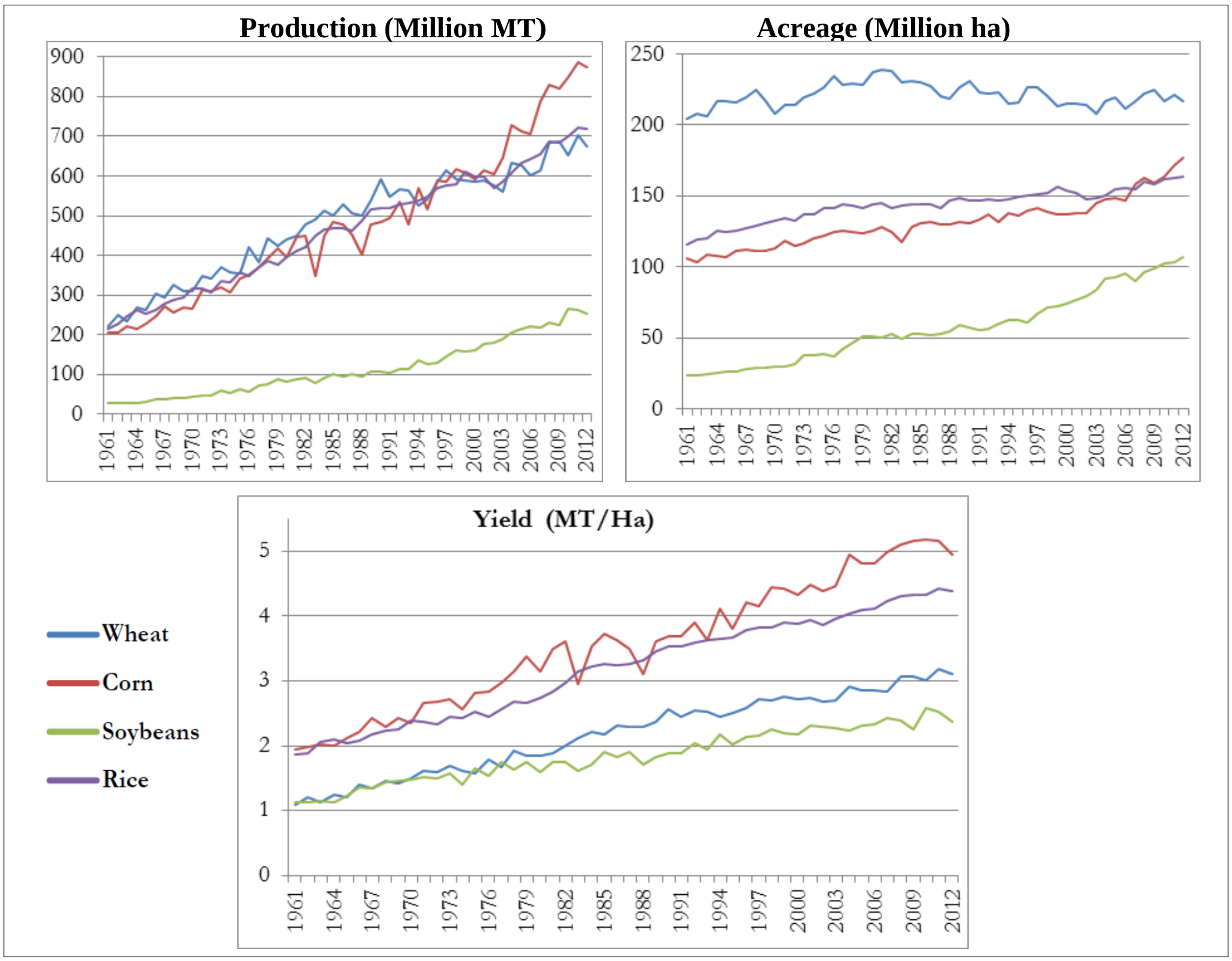

Figure 1.2. Global production, harvested acreage, and yield trends since the 1960s

Source: FAO (2012) and national data sources.

Acreage expansion and yield improvements have significantly increased global production for all four crops during this period. Comparing the 1961–1970 and 2001–2010 decades, for instance, aggregate global production has increased more than six times for soybeans, tripled for corn, and more than doubled for wheat and rice. Whereas most of the increase in wheat production comes from higher yields, the growth in soybean production is mostly attributed to acreage expansion. Global soybean acreage has more than tripled over the past five decades, while global corn acreage rose by about 40%. Some studies suggest that emerging biofuel markets and Chinese soybean imports are the major drivers of the acreage increases for corn and soybeans (Abbott et al., 2011). These changes in crop acreage have been achieved both by pulling marginal land into cultivation and by bidding land away from less competitive crops.

To this end, Figure 1.3 depicts the area changes of selected crops during the six year period between 2004/05 and 2010/11. Agricultural producers have so far mainly responded to the increase in food prices by bringing in more land into production. However, close to 30% of the increase in area of the high-demand crops in this six year period was composed of displaced low-demand crops. Figure 1.3 shows that the five major crops that have shown expansion in area cultivation added about 45 million hectares of land within these six years. Corn and soybeans alone have contributed close to 60% of the area increase during this period. It is likely that total cropland supply will be even more inelastic in the future due to population pressure, desertification and other climatic factors. This implies that the acreage response of countries towards high and volatile agricultural commodity prices will be predominantly via land reallocations. Closing yield gaps in several low-yield regions and further improving productivity in the already high-yield regions are, of course, additional potential responses towards such price dynamics.

Although production, acreage, and yield of all four crops seem to show an upward trend during the last five decades, a closer inspection shows that there exist year-to-year variations for all crops. In fact, Figure 1.4 shows that annual acreage changes for soybeans, corn and wheat have become more variable since about 2002 relative to the preceding five years. Moreover, the growth of planted wheat and rice acreages has been relatively more stable compared to that of soybeans and corn in the past two decades. The global soybean acreage has been steadily growing since about the mid-1990s except for a decline of about 5% in 2007. Planted corn area has also shown a consistent upward trend in the past decade except a slight decline in 2009. Periods of major acreage increase in global corn has usually been at a cost of soybean acreage, or vice versa. For instance, a close to 5% decline in global planted acreage for soybeans in 2007 was accompanied by an increase of about 7% in the global acreage for corn. This is due to the fact that the two crops are typically planted in similar seasons, have similar land requirements and are good substitutes for animal feed.

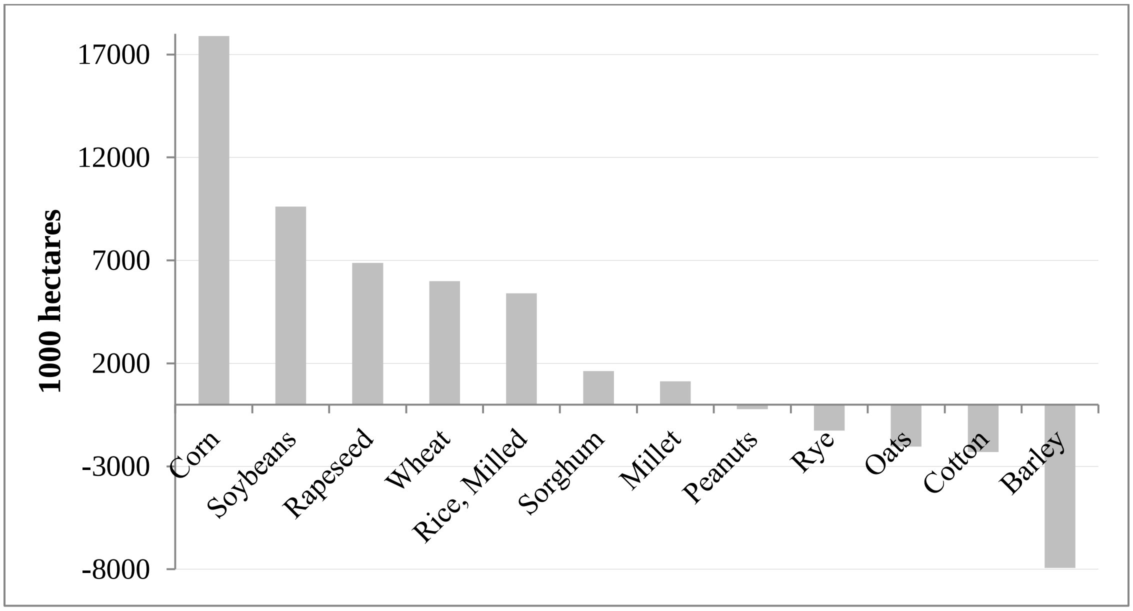

Figure 1.3. Total harvested area change for major crops in the world between 2004/05 and 2010/11

Source: Foreign Agricultural Service of the USDA

As the total global harvest quantity equals the product of area planted and yield per area planted, it is possible to decompose harvest fluctuations into an area and a yield component.[1] Figure 1.4 shows the annual fluctuations of these two variables. It becomes apparent that yield fluctuations are of slightly higher magnitude than area fluctuations for most crops except for rice, although for the latter they are of similar order of magnitude. Regarding corn, yield fluctuations seem to have decreased within the past two decades while area fluctuations have increased. Having a good prediction of acreage decisions therefore reduces the uncertainties regarding future harvests. This, in turn, allows a rough forecast on the next period's food supply situation which may already indicate possible shortages. Since an increase in productivity through technological progress and intensification is a rather long-term process, area expansion and re-allocation is the

[1] As opposed to the typical definition of yield as the ratio of harvest and area harvested, we use area planted instead, which is the proper decision variable of the farmer. Due to weather and pest events, farmers may harvest substantially less area than what was planted. Hence, harvested area contains more stochastic influences.

most important short-term decision variable for the farmer (Roberts & Schlenker, 2009; Searchinger et al., 2008).

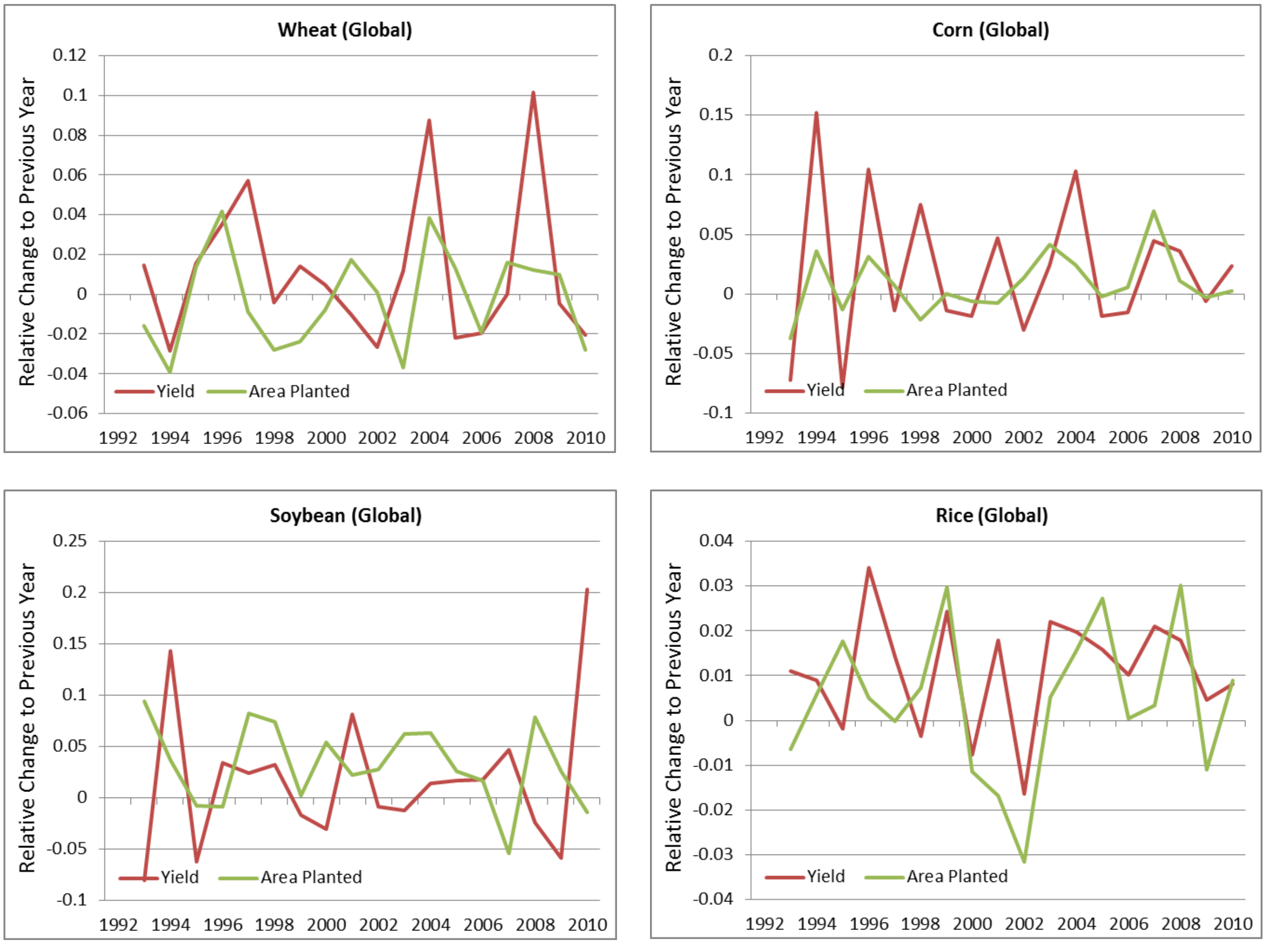

Figure 1.4. Annual fluctuations of global area planted and yield per area planted

Source: Authors' calculations based on generated and FAO (2012) data

1.3. Price expectation formation

The theory of price expectation lies at the center of any supply response analysis. The intrinsic feature of agriculture that there is a time lag between production decision and output realization means that agricultural producers need to make their harvest time price expectations during production decision time. Several approaches have been applied to model expectations of economic agents. Naïve, adaptive, quasi-rational, and rational expectations are the most commonly applied approaches in agricultural markets, which we will further discuss in subsequent chapters. We employ a variety of price expectation assumptions in our supply response analyses; planting period price is mostly our preferred proxy for producers' expectations.

Agricultural producers use different information when making their price expectations, which may include, among many, past trends, outcomes in related markets, media reports, weather, and published forecasts (Just & Rausser, 1981). Since obtaining and processing information is costly, however, it is unlikely that producers make use of all available information to form their price expectations (Orazem & Miranowski, 1986). This is even so in the context of smallholder farmers in developing countries where access to information and capital is limited. Thus, understanding what information set producers use and modelling how this information set is utilized in their production decisions have been an integral part of agricultural supply response models (Fisher & Tanner, 1978; Holt & McKenzie, 2003). Analysis of agricultural producers' actual price expectations and the distribution of their expectations relative to realized prices may assist agricultural economists and policy makers to deliver price outlook and price risk management strategies information, and researchers estimating supply response models to choose more appropriate specification of price expectation. Moreover, this thesis attempts to explain the role that information plays in the accuracy of agricultural producers, particular smallholder farmers, in their price expectations.

1.4. Objectives

Given the discussion in the previous sections, this thesis tries to answer the question, "how much of the global food supply change is driven by the international price dynamics?" More specifically, this study has the following three major objectives:

(i) To examine how food price risk– measured in terms of price volatility– and changes in price level affect supply, both in terms of acreage and yield, of key world staple crops.

This objective addresses two related research questions: First, because the majority of existing econometric analyses and the empirical literature focus on national acreage response to domestic prices, it tries to fill this research gap by exploring global annual and intra-annual acreage responses of the four key staple crops to international market prices. By applying the details of the crop calendar for major producing countries, we derive monthly patterns of acreage allocation and production at the global level. We therefore explicitly consider the role of seasonality on global grain supply by developing and estimating an intra-annual (monthly) acreage model in addition to the conventional annual acreage response model. Second, the thesis estimates global supply response of these key agricultural commodities employing a newly developed multi–country, crop– and calendar–specific, seasonally disaggregated panel data with price changes and price volatility applied accordingly. A dynamic panel econometric model, more specifically a system GMM technique, is used to estimate our dynamic supply response models. In addition to interpreting the results of our estimations, we use the estimated coefficients to address the question whether the recent increase in prices and price volatility is an opportunity or a challenge to agricultural producers and to the agriculture sector in general. Accordingly, we use simulation analyses to assess the overall impacts of recent agricultural commodity price dynamics, price level versus price volatility, on the supply of the key staple crops.

(ii) To develop an econometric model that enables forecasting of planted acreages of major staple crops two to three months before the planting season starts.

This objective attempts to develop a country and crop specific acreage response model for selected food crops for major producer countries. In particular, this study identifies appropriate specifications and factors affecting agricultural supply in *each country and each crop*. This allows us to account for the large heterogeneity in the countries' agricultural, political and economic systems using a country-specific model specification. The performance of the forecasting tool is assessed with ex-post prediction of acreage against historical data.

(iii) To model price expectation formation of smallholder farmers in the context of developing countries.

Each of the supply models of the above objectives requires some form of price expectation modelling. Yet, the theoretical and empirical literature is not conclusive regarding which expectation formation approach is appropriate. This objective analyzes price expectation formation in a more detailed manner for the case of Ethiopian smallholder producers where we consider particularly the fact that information is not costless. In other words, we consider expectation formation to be part of the farmers' economic decisions. This objective involves two related sub-objectives. First, it identifies the relevant variables that constitute the information set of a typical smallholder farmer in his/her price expectation formation. The importance of each of the elements in the information set is investigated. In other words, it addresses the question, "what information shapes smallholders' price expectations?" Second, we explain the role that information plays in the efficiency of smallholder farmers in their price expectations. This addresses the question of whether investing in acquiring information reduces the prediction errors of agricultural producers in the context of smallholder farmers in rural Ethiopia.

In doing so, the study analyses agricultural markets and food price volatility at international, national and household levels. The partial equilibrium supply response model helps to investigate changes in the land allocation and yield of major primary agricultural commodities in the major producer countries, which may result from changes in output prices and volatility. Shocks in supply (weather), demand (biofuel) or policy changes in one or more of these countries may trigger the volatility in output prices, which should be captured by the proxy for the price expectation in our subsequent supply models. The study further goes to the household level and assesses how smallholder farmers in a developing country form their price expectations. In general, the study gives due attention to short-term food price volatility and to major food crops including wheat, corn, soybeans, and rice.

1.5. Thesis outline

Following the preceding introductory discussions, the thesis is structured into four main chapters and a general conclusion chapter. Although the four chapters are related, they are self-contained papers that specifically address the above proposed research objectives.

Chapter 2 studies the global annual and intra-annual supply dynamics of the aforementioned four key staple crops. Abstracting from the 'external' weather and pest shocks that are hardly predictable some months in advance, this chapter focuses on acreage allocation decision as one key determinant of short-term supply. A unique feature of this chapter is that we have constructed monthly time series global planted acreage data since the 1960s. To this end, we use country–specific crop calendar to trace the annual harvested and/or planted acreage data back to the respective planting months of each crop. The crop-calendar generated data set enables us to analyze the variability of agricultural response to output prices and price risk across seasons and months.

Chapter 3 addresses a similar research question to that of chapter 2; however, besides acreage response, it further investigates yield and production responses to price and volatility. This chapter estimates global supply response of the key agricultural commodities employing a dynamic panel econometric model using a newly developed multi-country, crop-calendar–specific, seasonally disaggregated panel data with price changes and price volatility applied accordingly. Using the econometrically estimated coefficients of price levels and volatility, the chapter also assesses the net-impacts of the recent agricultural commodity price dynamics on acreage, yield, and production. We use a simulation analysis to measure the overall impacts of the 2006–2010 agricultural commodity price dynamics on the supply of the aforementioned key interest crops.

In chapter 4, we develop a country and crop-specific acreage forecasting tool for selected food crops for the major producer countries. It employs an Autoregressive Distributed Lag (ARDL) econometric model specification for each country and each crop. Thus, the respective acreage determinants are separately identified and used for forecasting. This allows us to account for the large heterogeneity in the countries' agricultural, political and economic systems in a country-specific model specification. The performance of the forecasting tool is assessed with ex-post prediction of acreage against historical data. The forecasting tool includes for major producer countries including USA, Brazil, Argentina, and the Russian Federation.

Chapter 5 addresses the third research objective discussed above. Each of the supply models of the previous chapters requires some form of price expectation modelling. Yet, the theoretical and empirical literature is not definitive regarding which expectation formation approach is appropriate. This chapter analyzes this issue in a more detailed fashion for the case of Ethiopian smallholder producers where we consider particularly the fact that information is not costless. In other words, we consider expectation formation to be part of farmers' economic decisions. The first section in this chapter identifies the relevant variables that constitute the information set of a typical smallholder farmer in his/her price expectation formation. It also investigates the role that information plays in the accuracy of smallholder farmers' price expectations. To this end, this study develops a theoretical model that demonstrates that smallholder farmers, who are assumed to be risk averse, invest in acquiring better price information to improve the quality of the price signal that they receive at planting season. A primary smallholder survey dataset is employed to empirically test this particular implication of the theoretical model.

Finally, chapter 6 presents the major findings of the entire study, with potential policy implications and further research topics.

2. Inter-and intra-seasonal acreage response to international food price changes

Abstract[*]

Understanding how producers make decisions to allot acreage among crops and how decisions about land use are affected by changes in prices and their volatility is fundamental for predicting the supply of staple crops and, hence, assessing the global food supply situation. This study makes estimations of monthly (i.e. seasonal) versus annual global acreage response models for the world's principal staple food crops: wheat, corn, soybeans and rice. Primary emphasis is given to the magnitude and speed of the allocation process. Estimation of intra-annual acreage elasticity is crucial for expected food supply and for input demand, especially in the light of the recent short-term volatility in food prices. The econometric results indicate that global crop acreage responds to crop prices and price risks, input costs as well as a time trend. Depending on respective crop, short-run elasticities are about 0.05 to 0.40; price volatility tends to reduce acreage for some of the crops; comparison of the annual and the monthly acreage response elasticities suggests that acreage adjusts seasonally around the globe to new information and expectations. Given the seasonality of agriculture, time is of an essence for acreage response. The analysis indicates that acreage allocation is more sensitive to prices in the northern hemisphere spring than in winter and the response varies across months.

JEL classifications: O11, O13, Q11, Q13, Q18, Q24

Key words: food price volatility, acreage response, price expectation, land use, food supply, international prices

[*] Most of the material in this chapter is drawn from our publication in *Agricultural Economics*: Haile, M. G., Kalkuhl, M. and von Braun, J. (2014), http://onlinelibrary.wiley.com/doi/10.1111/agec.12116/abstract.

2.1. Introduction

Prices of agricultural commodities are inherently variable. The variability of prices is mainly caused by the stochastic characteristics of weather conditions and pest infestations that influence harvest. It is furthermore exacerbated by the inelastic nature of demand and supply – in particular the inelasticity of regional production that is typically possible once a year. Some also argue that demand shocks are principal sources of price co-movements of several commodities (Gilbert, 2010). Besides these traditional causes for price fluctuations, agricultural commodities are increasingly connected to energy and financial markets, with potentially destabilizing impacts on prices (von Braun & Tadesse, 2012).

The aim of this chapter is to understand the global annual and intra-annual supply dynamics of the four most important staple crops, namely wheat, corn, soybeans and rice. These commodities are partly substitutable at the margin in production and demand, and constitute a substantial share of the caloric substance of world food production (Roberts & Schlenker, 2009). Abstracting from the 'external' weather and pest shocks that are hardly predictable some months in advance, we focus on the acreage allocation decision as one important determinant of short-term supply. For these and other unpredictable conditions that usually occur after planting the agricultural economics literature favored estimation of acreage over output response functions in order to understand crop production decision (Coyle, 1993).

As the total global harvest quantity equals the product of area planted and production per area planted, it is possible to decompose harvest fluctuations into an area and a yield component.[2] Figure 2.1 shows the de-composition of production fluctuations into these two variables over two periods since 1961. It becomes apparent that yield fluctuations are of higher magnitude than area fluctuations for all crops except for rice. While yield fluctuations have decreased for all crops in the second period, area fluctuations slightly increased for wheat and rice. Having a good prediction of acreage decisions therefore reduces the uncertainties regarding future harvests. Analyzing the magnitude and speed of global supply response is further important to understand price volatility and its implications to (global) food security: The more inelastic (annual) supply

[2]As opposed to the typical definition of yield as the ratio of harvest and area harvested, we use area planted instead, which is the proper decision variable of the farmer. Due to weather and pest events, farmers may harvest substantially less area compared to the planted area. Hence, harvested area contains more stochastic influences.

is the stronger is the degree that harvest and demand shocks translate to price spikes. Nevertheless, if supply is elastic and responds to annual and intra-annual price dynamics, harvest failures in one part of the world can be absorbed by increased production somewhere else. This is true for demand shocks as well.

Since an increase in productivity through technological progress and intensification is a rather long-term process, area expansion and re-allocation is the most important short-term decision variable for the farmer (Roberts & Schlenker, 2009; Searchinger et al., 2008). Hence, our research focuses on two crucial questions regarding the global short-term supply of staple crops: (i) How *strongly* does global acreage respond to (expected) international prices and price changes and (ii) how *fast* do farmers react to price changes in terms of acreage adjustments?

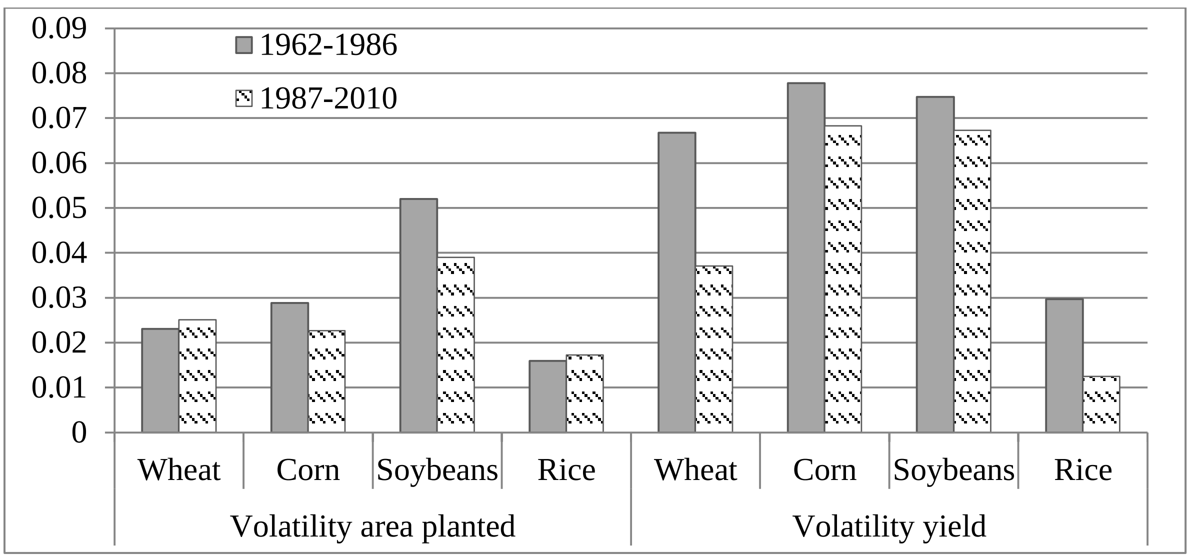

Figure 2.1. Volatility of global area planted and production per area planted

Note: Volatility is measured as the standard deviation of the annual log changes
Source: Authors' calculations based on generated database from FAO (2012) and national data sources.

Existing econometric analyses focus on *national* acreage response to domestic prices. As most countries exhibit only one major planting and harvesting season (which hardly differs among intra-country regions), seasonality of supply does not need to be accounted for in studies focusing on a single country. On a global scale, however, planting and harvesting occurs throughout the entire year, which has an important implication: While national production is highly inelastic until the next harvest in about a year, global planting can instantaneously respond to current harvests and prices which, in turn, shapes the supply situation in three to four months' time. Additionally, existing national supply analyses cannot be used to calculate a global (annual) supply elasticity as they: (i) differ in their modelling approaches, (ii) consider different prices, in particular, when focusing on domestic spot prices that might be poorly integrated with world market prices, and (iii) do only cover few countries.[3]

The objective of this chapter is therefore to fill this research gap by exploring *global annual and intra-annual* acreage responses of the four key staple crops to international market prices. By applying the details of the crop calendar for major producing countries, we can derive monthly patterns of acreage allocation and production at the global level. We therefore explicitly consider the role of seasonality on global grain supply by developing and estimating (i) an annual acreage model, (ii) an intra-annual (monthly) acreage model, and (iii) a month-specific supply model (that gives supply elasticities at typical planting months of each crop).

Finding a robust answer to our research questions requires testing for different price expectation formation models as expected prices are not directly observable. We further consider the impact of uncertainty (or risk) in the price expectation process that might influence the farmers' acreage decisions. While upward output price trends are incentives for agricultural producers to make agricultural investments such as expanding acreage, output price volatility introduces risks that affect a risk-averse agricultural producer (von Braun & Tadesse, 2012). This study, therefore, investigates the responsiveness of global agricultural cropland to changes in output prices and the uncertainty therein. Estimation of intra-annual acreage elasticity is crucial especially in the light of the current short-term volatile food prices for policy makers concerned about food security, agricultural investors, and for the agribusiness sector including input supply industries.

The chapter is structured as follows: the following two sections provide a brief overview of temporal and spatial global acreage dynamics where we explain the functioning of the crop calendar. Next, we introduce the empirical framework with some theoretical considerations about acreage response and explain our data sources. After discussing the econometric results for different model specifications, we conclude with some further suggestions regarding global food supply and food price volatility.

[3]An exception is a global supply analysis by Roberts and Schlenker (2009) which, however, focuses on annual calorie-equivalent supply response and neglects seasonality.

2.2. Global acreage change and price dynamics

The causes of high agricultural commodity prices are debated. Demand shocks that have persisted in the past decade played a significant role: the rapid worldwide shift towards corn use for fuel, aggressive Chinese soybean imports, and higher demand for food (especially meat) due to higher income levels in several emerging economies are some of these demand-side causes (Abbott et al., 2011). These surges in demand, accompanied by the growing world population, have a remarkable bearing on the global land allocation. For instance, the additional Chinese soybean demand was to a large extent met by soybean acreage expansion in Latin America (Abbott et al., 2011). There have also been several other acreage expansions and reallocations all over the world following the recent output price variations. As a result, there have lately been remarkable foreign agricultural investments in many developing countries, primarily focusing on growing high-demand crops including corn, soybeans, wheat, rice and many other biofuel crops (von Braun & Meinzen-Dick, 2009).

On the supply end, the four crops corn, wheat, rice and soybeans, which are the subject of this study, constitute a sizable share of global area and production. Corn, wheat and rice, respectively, are the three largest cereal crops cultivated around the world. According to data from FAO (2012), they make up more than 75% and 85% of global cereal area and production in 2010, respectively. About one third, of both the global area and production, of total oil crops is attributed to soybeans.

Figure 2.2 depicts the trends of global acreages of selected crops and of total arable land since 1961. Until 1985, total arable land expanded with increasing demand for cereals and oilseeds. However, arable land has become more and more binding as cultivation of new land could not compensate for losing land due to desertification and urbanization (Hertel, 2011). While new acres have been the principal sources of area expansion at the global level, area reallocation is more important for countries with arable land constraints such as the United States (Abbott et al., 2011). The same study describes that total cropland area in these countries has been stable over the past two decades and acreage expansion of some crops has been at the expense of 'low-demand crops' such as barley and oats. It is likely that total cropland supply will be even more inelastic in the future due to more population pressure, desertification and changing climatic factors. This implies that the acreage response of countries towards high and volatile agricultural commodity prices will be predominantly via land reallocations.

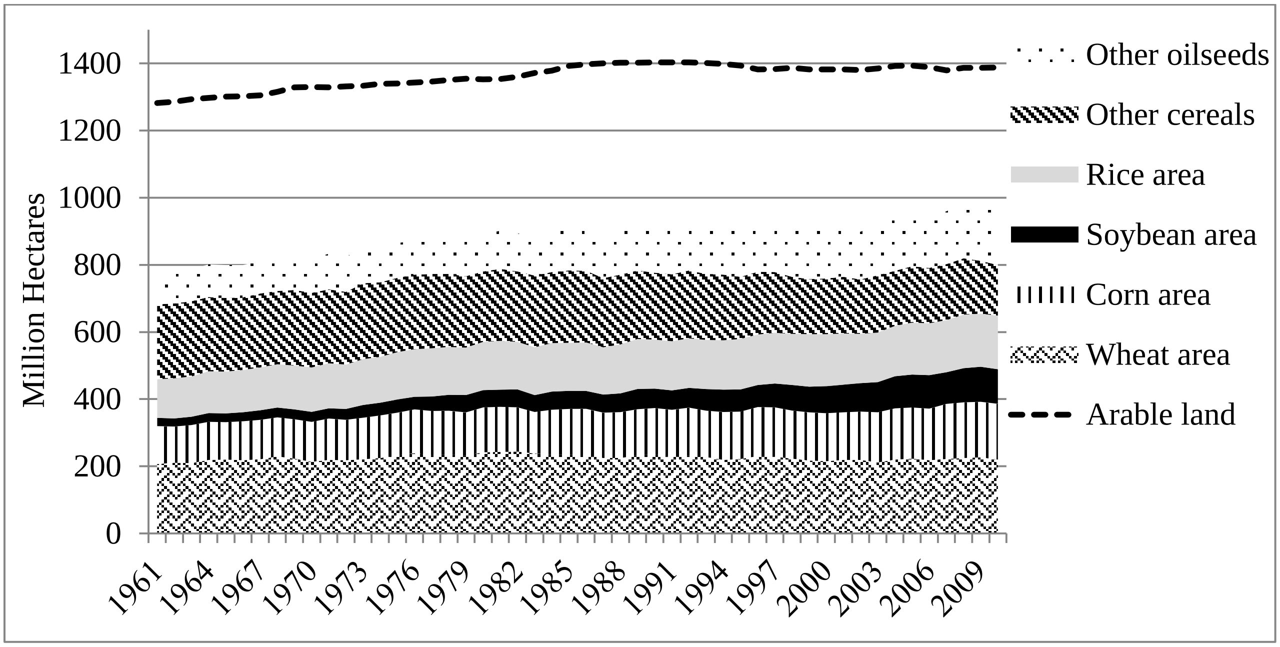

Figure 2.2. Trends in total arable land and global acreages of selected crops (1961–2010)

Source: FAO (2012)

This study builds on the extensive literature on the estimation of land allocation decisions in agricultural economics. The acreage response literature has actually gone through several important empirical and theoretical modifications. These include acreage response studies in line with the Nerlovian general supply response function (Askari & Cummings, 1977; Nerlove, 1956) and recently in a theoretically more consistent mode that integrate both producer and consumer economic behavior (Chavas & Holt, 1990; Chavas & Holt, 1996; Lin & Dismukes, 2007). Nevertheless, there are various reasons to reconsider the research on acreage-price relationships. The majority of the previous empirical literature investigating acreage response focuses largely on particular crops for a few countries such as the United States (Arnade & Kelch, 2007; Liang et a.l, 2011), Canada (Coyle, 1992; Weersink et a.l, 2010) and few others (Lansink, 1999; Letort & Carpentier, 2009). To our knowledge, there are few studies that estimate acreage elasticity at the country level (e.g. Barr et al., 2009; Hausman, 2012), and none at the global level. The effect of price volatility is usually considered as a microeconomic problem for producers. However, there are several factors (such as foreign direct investment in agriculture) that render the global and country level agricultural production to be equally affected by price volatility as the farm level production. Given that previous analyses show the acreage effect of price volatility at micro and national level, we ask whether this effect ensues at the global scale. The analysis at global scale appears to be even more important as the global supply response on price changes and price risk influences local food availability through market integration. Such global analysis involves data aggregation that could result in potential loss of efficiency of estimates. Nevertheless, since each producer faces the same international price in our global level analysis, the potential aggregation bias will be less problematic.

2.3. Monthly patterns of global cropped acreage

Global crop acreages, both sown and harvested, are neither uniformly distributed among all months within a year nor across geographical regions in the world. The global cropped acreage is rather concentrated in a few months depending on agro-ecological zones of the key producer countries. Since global harvested and planted acreage data are published annually, we construct a monthly database using country-specific crop calendar to trace the annual harvest and acreage data back to the respective harvesting and planting months for each crop (see Tables A5–A8 in Appendix I). The countries for which we have compiled crop calendar data comprise more than 80% of both the world production and sown acreage for each of the four crops. A symmetric multangular probability distribution is used to assign values to each month in case of multiple planting and harvesting months. The acreage data for countries in the 'rest-of-world' (ROW) category are evenly distributed across all months within a year.[4] Area harvested is used as a proxy for planted area if data for the latter are not available from the relevant national agricultural statistics. As we have area planted for many countries, the proxied area amounts to roughly one quarter of the total global area (for soybeans this number is even lower, 7%). The proxied area may introduce estimation bias if the deviation between planted and harvested acreage is linearly correlated with any of the independent variables in our acreage models. Although it is likely that this deviation is correlated with spot prices at harvesting period, there is

[4] Although Tables A5-A8 in Appendix I include crop calendars for more countries, we assigned former Soviet Union countries and countries with a global acreage share of less than half a percent in the 'rest-of-world' (ROW) category for the empirical analyses in this study.

no *a priori* reason to expect such correlation with expected prices at planting time that are used in our model.[5]

Figure 2.3 displays the average annual global acreage and production shares of each month for the period between 2001 and 2010. The figure shows that most of the global planted acreage of these crops is cultivated in two major crop seasons, winter and spring.[6] While most of the global wheat is sown in winter, with a peak in October, the majority of the global corn is planted in spring, mainly in April and May. Nevertheless, global soybean is cultivated both in spring and winter seasons, with major peaks in May and November, respectively. Rice planting is relatively more spread throughout the year with a peak in the early summer. There are several regions in diversified agro-ecological zones where rice can be planted all year round.

Figure 2.3 also illustrates how the growing periods vary across crops. Considering the major planting and harvesting months, the growing periods range from as short as 3-4 months for rice, soybeans and spring wheat to as long as 8-9 months in the case of winter wheat. Unlike summer crops, which continuously grow from sowing to harvesting, winter wheat is sown in fall and stays dormant during the winter until it resumes growing in spring of the following year. What is also clear from Figure 2.3 is that no major planting and harvesting exists in the world for about a third of the year, December to March. For instance, only about 6% and 7% of the total wheat area and production during the last decade are planted and produced in these four months, respectively.

[5] We calculated the linear correlation of the planted-harvested acreage deviation and the planting period prices of the selected crops for the United States and Brazil: the simple correlation coefficients range between 0.07-0.52.
[6] In this study “winter” and “spring” refer to the respective seasons in the northern hemisphere.

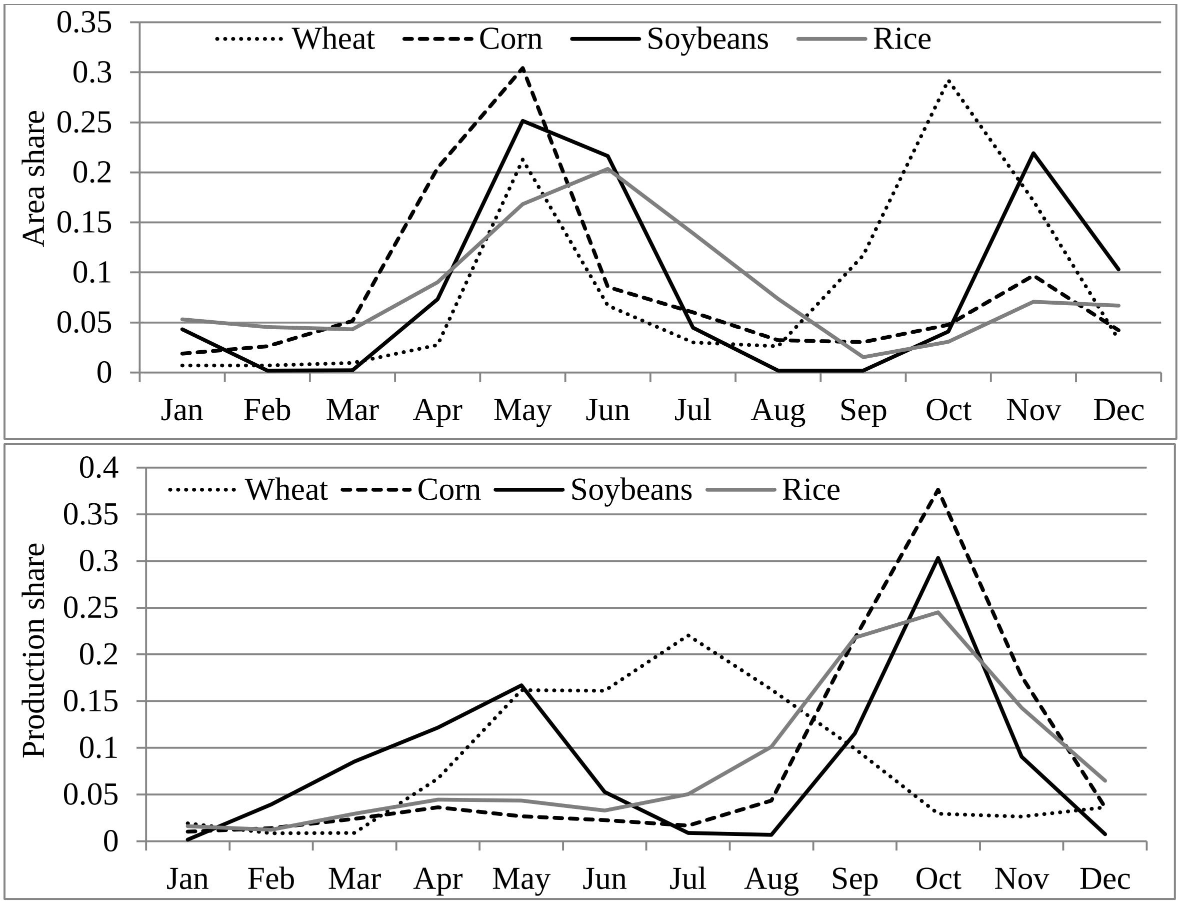

Figure 2.3. Global average monthly-planted acreage (top) and production (bottom) shares of selected crops for the period 2001–2010

Source: Authors' calculations based on global crop calendar information and data from FAO (2012**)** and national data sources.

With regard to the geographical distribution, the global acreage shares of individual countries illustrate that cultivation of these crops is concentrated in a few countries (see Tables A5–A8 in Appendix I). It can be seen that the top five soybean growing countries -United States, Brazil, Argentina, China and India- cultivated close to 90% of the global soybean acreage planted in 2008. Above 60% of the global cultivated land for both corn and wheat is also found in the top six producers including the European Union (EU-27) as one entity. Similarly, close to half of the global rice acreage is planted in China and India. Therefore, it is sufficient to use data from key producer countries in order to get a good representation of global cultivations for these crops. Adding a spatial dimension to Figure 2.3 above shows which countries dominate the cultivation and hence the production in those peak planting and harvesting months. While countries in the

North produce the larger share of winter wheat and rice, the global soybean and corn production is nearly evenly shared between the two hemispheres.

Our crop calendar data has some limitations, however. First, the monthly disaggregation does not capture any change of planting dates over time. Early or delayed planting and harvesting may occur for several reasons such as climatic and agronomic factors, ownership of tractors, availability of inputs, technological change and other socio-economic reasons which are not predictable and which vary across countries and over time. As it is difficult to account for these complexities, the monthly data are best approximations for the respective months rather than accurate acreage values. The other limitation is that the crop calendar observations are specified at the national level despite planting and harvesting month variations within countries. Nevertheless, the crop calendar data set enables investigation of intra-annual and inter-national acreage responses to output prices and their variability. The disaggregated data is central to analyze the variability of agricultural response to output prices and price risk across seasons and months.

2.4. Empirical Framework

2.4.1. Theoretical base

Modelling crop production in terms of acreage response is preferred to output supply since, unlike observed output, planted area is not influenced by the conditions after planting (e.g. weather, pest) (Coyle, 1993). Agricultural producers do also respond to output prices primarily in terms of changes in acreage allocation (Roberts & Schlenker, 2009; Searchinger et al., 2008), especially in the short-term. Several agricultural economists adopted Nerlove's partial adjustment and adaptive expectations model (Nerlove, 1956) to estimate acreage response equations, with various theoretical and empirical modifications (Chavas & Holt, 1990; Chavas & Holt, 1996; Lin & Dismukes, 2007). This section describes the theoretical framework for a profit maximizing farmer who chooses the optimal allocation of land under crop price uncertainty. Uncertainty is a typical feature of agricultural production for several underlying reasons (Moschini & Hennessy, 2001). The profitability of a land allocated to a certain crop is affected by the uncertainty of the crop's price that in turn affects the acreage allocation decision of the producer.

Consider a multi-output expected profit Π maximizing agricultural producer with a fixed total cropland $\bar{l}$ that can be allocated for N crops where l_i denotes the acreage allocated for the *i*-th crop (Arnade & Kelch, 2007; Chambers & Just, 1989). Assuming a mean-variance approach (Coyle, 1992, 1999; Lansink, 1999), the risk preferences of the farmer are specified in terms of a utility function where the certainty equivalent of the expected utility maximization is expressed in term of the first two moments of profit (mean, $\bar{\Pi}$ and variance, σ_{Π}^2)

$$E\ U(\Pi) = E\ \Pi(\boldsymbol{p}, \boldsymbol{w}, l, \boldsymbol{z}) - \frac{1}{2}\ \alpha\ \sigma_{\Pi}^2 \qquad (2.1)$$
$$s.t. \textstyle\sum_{i=1}^{N} l_i \leq \bar{l}$$

where $\Pi(\boldsymbol{p}, \boldsymbol{w}, \boldsymbol{l}, \boldsymbol{z}) = \boldsymbol{p}'\boldsymbol{y}(\boldsymbol{x}, \boldsymbol{l}, \boldsymbol{z}) - \boldsymbol{w}'\boldsymbol{x}$ is the farmer's profit, $\boldsymbol{p}$ and $\boldsymbol{y}$ are vectors of output price and quantity, respectively; $\boldsymbol{w}$ and $\boldsymbol{x}$ are vectors of input price and quantity, respectively; $\boldsymbol{l}$ denotes the vector of land which in its sum is fixed by $\bar{l}$ but allocatable; $\boldsymbol{z}$ is a vector of other fixed inputs (machinery and equipment); and α is a measure of risk aversion representing risk averse ($\alpha > 0$), risk neutral ($\alpha = 0$), and risk loving ($\alpha < 0$) producers respectively.

Assuming that crop prices **p** remain the only random variables in the model (input prices are treated as exogenous), the expected mean and variance of profit are[7]:

$$E(\Pi) = E[\boldsymbol{p}]'\boldsymbol{y}(\boldsymbol{x}, \boldsymbol{l}, \boldsymbol{z}) - \boldsymbol{w}'\boldsymbol{x} \qquad (2.2)$$
$$\sigma_{\Pi}^2 = \boldsymbol{y}'\boldsymbol{\Omega}_{\boldsymbol{p}}\boldsymbol{y}$$

where Ω_p denotes the covariance matrix of crop prices and Ω_{pij} refers the (co)variances of the prices of crops i and j. Using the above first and second moments of the profit function, we obtain the following optimal allocation of land to crop *i* after optimization:

$$l_i^* = l_i^*(E[\boldsymbol{p}], \boldsymbol{w}, \Omega_p, \bar{l}, \boldsymbol{z}) \qquad (2.3)$$

Unlike the land allocation functions resulting from the traditional price-certainty models, the corresponding functions from the mean-variance approach are affected by output price uncertainty. The first-order condition with respect to the acreage allocation, $\boldsymbol{l_i}$ indicates that higher own price variance or higher positive covariances of the price of a given crop with other

[7] Uncertainty regarding yields may also play a role in the allocation decision but is not dealt with here. The formal integration of yield risk is similar to price risk with a further consideration of co-variances between yield and prices.

crops' prices require a lower shadow price of land.[8] Holding the shadow price of land constant, this implies that acreage allocated to i-th crop declines with higher variance or positive covariances of crop prices. However, the results of the price-certainty model can be obtained either if the risk aversion measure α is zero or if the covariance of crop prices $\boldsymbol{\Omega_p}$ is a null matrix. Risk aversion implies that marginal costs are lower than output prices, implying that acreage and hence output is lower than optimal output under risk neutrality (Lansink, 1999).

2.4.2. Model Specification

Price expectations and risks

The farmer has to make his optimal crop acreage choices subject to output prices that are not known at the time when planting decisions are made. Thus, expected rather than realized output prices are used for decision making. Neither is there an *a priori* technique to identify the superior price expectation model nor does the empirical literature provide unambiguous evidence on which expectation model to use for empirical agricultural supply response estimation (Nerlove & Bessler, 2001; Shideed & White, 1989).

Since expected prices are not realized at planting time, we employ several alternative expectation assumptions in our empirical global acreage response model. First, we use the price of the harvesting period prior to the planting period as proxy for expected harvest crop prices (Coyle et al., 2008; Hausman, 2012). This corresponds to a naïve expectation model where farmers base their future price expectation on the most recent harvest price. Second and in a somewhat different fashion, we consider crop prices during the pre-planting month(s). These prices contain more recent price information for farmers and they are also closer to the previous harvest period, conveying possibly new information about the future supply situation. Third, when applicable, the futures prices at harvesting time traded in the months prior to planting are used to represent farmers' price expectations (Gardner, 1976).

As mentioned above, this study captures price risk (uncertainty) using a measure of international price instability. We measured price risk as the standard deviations of the changes in the logarithmic output prices of the previous 12 months (Gilbert & Morgan, 2011). In addition, the

[8] The first-order condition is given by $\{E[p_i] - \alpha\Omega_{pi}\boldsymbol{y}\}\frac{\partial y_i}{\partial l_i} = \phi$, where ϕ is the shadow price of land.

co-variances between expected crop prices were used as additional variables to capture price risk.

Global acreage estimation

We consider a reduced-form representation of agricultural response according to:

$$l_{it} = \alpha_i l_{it-1} + \sum_{j=1}^{4} \beta_{ij} E[p_{jt}] + \sum_{j=1}^{4} \delta_{ij} \Omega_{jt} + \theta_i Z_{it} + \gamma_i t_i + c_i + \varepsilon_{it} \qquad (2.4)$$

where l_i denotes the acreage planted to the i-th crop (1=wheat 2 = corn, 3 = soybeans, and 4 = rice), $E[p_j]$ is the expected price for the j-th crop, Ω_{jt} is the variance of crop prices, Z_i denotes production costs (fertilizer price index), and ε is the error term. The time trend γ captures the effect on acreage of technological change over time and of the increase in output demand resulting from increases in demand for biofuel, income and population. Since some crops are substituted into rotations relatively easier than others, we include lagged own crop acreages in order to control for such adjustment costs.

We do not impose any symmetry constraints on cross-price elasticities that would follow from a homogenous production function. Instead, we use a less restrictive reduced-form approach as other competing crops are not integrated (the four considered crops contribute to roughly 40 % of total arable land, see Figure 2.2). Furthermore, world-market prices instead of domestic producer prices are used. Although farmers respond to expected domestic producer prices rather than (expected) world-market prices, we are interested in the global supply response to world market prices, which might differ from the domestic producer prices due to imperfect price transmission and integration into the global market.

The basic econometric approach in equation (2.4) is modified to three specifications that focus on different time scales of acreage response given in Table 2.1 below.

Table 2.1. Description of estimated models

Item	Annual Model (t on annual basis)	Intra-annual Model (t on monthly basis)	
		(1)	(2)
Dep. variable	Annually aggregated sown acreage	Monthly sown acreage	Sown acreage for typical planting months
Proxies for price expectations	Annual average prices at the year before planting	Monthly prices 1 month (wheat, rice) and 2 months (corn, soybean) before planting month	Monthly prices 1 month (wheat, rice) and 2 months (corn, soybean) before planting month
Price risk	SD of monthly price returns in the previous year	SD of price returns in the 12 months preceding the start of the planting period	SD of price returns in the 12 months preceding the start of the planting period
Lagged acreage	Acreage in the year before planting	Acreage in the same month of the previous year	Acreage in the same month of the previous year
Production costs	Annual average fertilizer price in the year before planting	Monthly fertilizer price in the month before planting	Monthly fertilizer price in the month before planting
Selected year dummies	Yes, crop specific year dummies	No	Yes, crop specific year dummies
Monthly dummies	No	Yes, to consider seasonal planting pattern	No
Output	Annual acreage elasticties	Average monthly acreage responses	Month-specific acreage response

Note: To save degrees of freedom and due to problems of high multicollinearity problem the cross-price variances, $\boldsymbol{\Omega_{ijt-1}}$ for $\boldsymbol{j \neq i}$, are dropped from the annual regressions.

2.4.3. Data

The econometric model relies on a comprehensive and elaborate database covering the period 1961–2010. The empirical model utilizes global and country-level data to estimate global acreage responses for the key world crops. While data on planted acreage were obtained from several relevant national statistical sources[9], harvested acreage for all countries were obtained

[9] These data sources are available in Appendix I (Table A9). In order to assess the quality of the cultivated acreage data, we compared different data sources (National Statistics, FAO and USDA) with respect to data on area harvested, as these are reported in all sources. We found the data to be broadly consistent. This could be indicative

from the Food and Agricultural Organization of the United Nations (FAO) and the United States Department of Agriculture (USDA). The crop-calendar for emerging and developing countries is obtained from the General Information and Early Warning System (GIEWS) of the FAO, and the Office of the Chief Economist (OCE) of the USDA is the source for that of the advanced economies. The crop calendar is further modified with expert knowledge on planting and harvesting periods from Bayer CropScience AG. The international spot market output prices, crude oil prices and fertilizer price indices were obtained from the World Bank's commodity price database. All commodity futures prices were obtained from the Bloomberg database. Finally, the US Consumer Price Index (CPI) used in this study was obtained from the US Bureau of Labor statistics.

The spot and futures crop prices, crude oil price and fertilizer price indices used in our estimation were all in real terms - deflated by the US CPI. The price of crude oil as well as fertilizer price indices are used as proxies for production costs which otherwise would not be captured. The crude oil price, as defined by the World Bank, refers to the average spot prices of Brent, Dubai and West Texas Intermediate with equal weights. The fertilizer price index, which is also obtained from the World Bank price database, contains the prices of natural phosphate rock, phosphate, potassium and nitrogenous fertilizers.

2.5. Results and Discussion

In the following section, we discuss several regression results to highlight the relationship between acreage, prices and price uncertainty. A standard approach to estimate such acreage response model is the seemingly unrelated regressions (SUR). However, we chose single equation methods of estimation. This is primarily for three reasons: the Breusch-Pagan test does not show significant correlation of residuals across the acreage equations[10]; a misspecification in one of the acreage equations in the system generally results in inconsistent estimates for the other equations (Coyle et al., 2008); and the explanatory variables are highly correlated across the

of the reliability of the data from the national statistical agencies. Few exceptions where deviations are higher than 5% include wheat in Argentina, corn in Japan, and Rice in Mexico. The USDA data for Turkey and Uruguay seems to deviate from the other sources.

[10] For instance the Breusch-Pagan test of independence of residuals in the annual acreage response model has a chi-squared statistic of 8.16 with P-value = 0.23.

equations. Thus, the efficiency gains from SUR will be small and single equation estimations are more robust.[11]

We have conducted the standard statistical unit root tests, augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests (Dickey & Fuller, 1979; Phillips & Perron, 1988), for each time series in the acreage response models of all four crops. The unit root test results in Table 2.2 indicate that the entire price and the annual global acreage variables of all crops are non-stationary series and are integrated of order 1. However, the monthly price volatility and the intra-annual acreage variables of all four crops were found to be stationary series.[12] The typical solution to avoid spurious regression resulting from a non-stationary time series, but not cointegrated, is differencing the series until we get a non-stationary series, I(0). Thus, we included the first order difference of the I(1) variables in the annual model. However, if either the dependent or the independent variable or both is stationary, which is the case in the intra-annual specifications of this study, then the regression is misspecified by differencing the series. By first differencing, we are imposing the constraint that the parameter on the lagged variable is one, which may not be true if the series is stationary. In such circumstances, including lagged values of the dependent and independent variables as regressors helps to avoid the problem of spurious regression. In this case, a set of parameters for which the error term is stationary exists and the t-statistics for the individual coefficient estimates will have the usual asymptotic normal distribution. Our intra-annual model specifications have both the lagged dependent and independent variables as explanatory variables and thus the estimated coefficients are asymptotically consistent.

All acreage and price variables (except for price volatilities, which are rates) are specified as logarithms in the econometric models of the proceeding discussion. Hence, the estimated coefficients can be interpreted as short-run elasticities. Depending on the disaggregation method, annual as well as monthly acreage elasticities are estimated. As the price co-variance terms cause problems of high multicollinearity and turned out to be insignificant, we omitted them. Since the lagged endogenous variable implies autocorrelation in our econometric estimations, we employed the Newey-West autocorrelation adjusted standard errors.

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[11] We provide results from SURE as Appendix I (Table A1) for the annual model where the equations contain slightly different variables: the results are quite robust.

[12] The Phillips-Perron test results are consistent with those of the Augmented Dickey-Fuller test results reported in Table 2.2.

Table 2.2. Unit root (ADF) test statistics *(Ho:* unit root)

	Intra-annual model		Annual Model			
Variable	**Non-trended model**	**Trended model**	**Non-trended model**		**Trended model**	
			Level	*First difference*	*level*	*First difference*
Wheat acreage	−17.02	−17.13	−1.79	−3.59	−1.89	−3.68
Corn acreage	−15.98	−17.26	0.12	−3.97	−1.64	−3..92
Soybean acreage	−10.22	−17.38	−1.02	−3.85	−1.46	−3.96
Rice acreage	−15.63	−16.10	−1.93	−3.82	−2.42	−3.98
Wheat price	−2.13	−2.86	−1.31	−4.48	−1.99	−4.47
Corn price	−1.88	−2.81	−1.18	−3.66	−1.65	−3.65
Soybeans price	−2.14	−2.75	−1.24	−3.29	−1.56	−3.27
Rice price	−1.80	−2.50	−1.39	−5.58	−2.32	−4.41
Fertilizer price	−2.50	−2.43	−2.26	−5.58	−2.20	−4.29
Wheat price vol.	−3.42	−3.70	−2.15	−4.32	−2.71	−4.31
Corn price vol.	−4.31	−4.76	−2.19	−4.55	−2.67	−4.48
Soybeans price vol.	−4.37	−4.67	−2.38	−4.64	−2.35	−4.58
Rice price vol.	−4.99	−4.98	−3.24	−5.58	−3.20	−5.51
Critical value (5%)	***−2.9***	***−3.5***	***−2.9***	***−2.9***	***−3.5***	***−3.5***

Notes: Critical values are taken from Fuller (1976, p. 373). The results are ADF tests with three lag lengths: We also checked ADF tests with different lag lengths for all variables. The unit-root test results are consistent across these specifications except for the annual price volatility variables whereby the ADF test results with no lag values seem to show existence of stationary series in these four variables.

2.5.1. Annual acreage response

The annual regression gives a conventional estimate of supply elasticities that indicate how annual global acreage changes in response to changes in output price expectation. To our knowledge, this is a first study to estimate acreage elasticities at a global scale. Additionally, short-term price movement indicators are considered to assess the impact of price risk or unpredictability of prices.

Table 2.3 shows the global annual acreage response results. We considered planting year cash prices (in the year before harvesting) as the expected harvest period prices. Since most of the sowing for the harvest of a specific year for wheat, corn and soybeans occurs during the spring of the same year or during the winter of the previous year, we lagged both spot prices and volatility. As rice is planted in most of the months throughout the year, we use the same-year values. We alternatively considered harvest time futures prices, observed in the months when planting decisions are made, as proxy for expected prices at planting time. As these periods differ from country to country, we use the planting and harvesting periods of the US as a reference since it accounts for a large share of global production of the crops under consideration. We also considered futures contracts traded in the US. While, in the case of wheat, the expected prices are derived from the average July wheat futures traded from October to December, the futures prices for corn and soybeans are the average December corn futures prices observed from March to May and the average November soybeans futures prices observed from April to June, respectively. We failed to find a significant area-price relationship using these futures prices, which could imply that several agricultural producers do not make use of futures prices information in forming price expectations. Indeed, futures prices are good proxy for expected prices for those producers in countries where the domestic price is strongly linked to the futures prices, i.e. where the maturity basis is constant. Although the farmers in advanced economies widely participate in the futures markets and the futures prices are linked to the cash prices, this is not the case in several developing countries.

Table 2.3. Annual global acreage response estimates

Variables	**Wheat**	**Corn**	**Soybeans**	**Rice**
Acreage (t-1)	-0.262**	-0.242*	-0.348*	-0.149
	(0.102)	(0.133)	(0.179)	(0.133)
Wheat price	0.088***	-0.108***	0.025	-0.554*
	(0.032)	(0.033)	(0.069)	(0.027)
Corn price	-0.005	0.179***	-0.194**	0.026
	(0.032)	(0.033)	(0.086)	(0.023)
Soybean price	0.033	-0.02	0.374***	0.022
	(0.031)	(0.031)	(0.104)	(0.021)
Rice price	-0.008	0.00	-0.003	0.022*
	(0.017)	(0.018)	(0.029)	(0.011)
Fertilize price index	-0.023**	0.017	-0.042*	0.013
	(0.013)	(0.011)	(0.024)	(0.008)
Own price volatility	-0.798*	-0.618**	-1.417*	-0.397***
	(0.470)	(0.311)	(0.745)	(0.110)
Time trend	-0.0*	0.0	0.0	-0.0*
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.41	0.53	0.55	0.36
N		48		

Notes: Figures in parentheses are autocorrelation adjusted standard errors. Selected year dummies were also included for each specification. $^*P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$.

The following discussion relies on the results obtained from the specifications with spot prices.[13] The regression estimates show that all the acreage responses to own prices are statistically significant and positive, consistent with economic theory. The short-run acreage responses to own prices range from 0.02 (rice) to 0.37 (soybeans). The results also show that the statistically significant cross-price acreage coefficients are consistent with economic theory: although they are not symmetric, the area responses to competing crop prices are negative. In this regard, expectations about wheat prices seem to be important for all but soybean crop acreages. Expectation of higher wheat prices encourages cultivation of more land for wheat production. The cross price coefficients suggest that shifting away land from corn and rice cultivation contributes to this additional land for wheat production. Besides encouraging more land to corn cultivation, the results also show that higher corn prices lead to less land for soybean production. Own price volatility reduces global crop acreage for all crops. The respective estimated coefficients of own price volatility range between -0.40 for rice and -1.42 for soybeans. Fertilizer prices are statistically significant for the global wheat and soybean acreages in the annual model (at the 10% level for the soybean model). As described above both the dependent variable, sown area, and its lagged independent variable are first-differenced to avoid spurious results due to unit root. The coefficients of the lagged acreage are negative for all crops and statistically significant for all crops except for rice. The interpretation is that a higher acreage growth in a certain year is associated with a lower growth in the coming year. This may be indicative of the cyclical (cobweb) nature of agricultural production.

2.5.2. Monthly acreage response

The annual regression is able to predict global annual acreage changes based on averaged annual prices. One important feature of the crop calendar and the resultant disaggregated data is that it allows calculating short-term supply elasticities on a monthly basis using information on prices and other factors that exhibit more intra-annual fluctuation. This will help understand the magnitude and the speed of the farmers' response to prices. We will present two different estimations: the first gives monthly price elasticities of crop acreage (represented as intra-annual supply elasticity in Table 2.4); the second estimates are month- specific elasticities (Table 2.5).

[13]Results where we used futures prices as proxy for expected prices are available in the Appendix (Table A2).

Intra-annual supply elasticities

The advantage of estimating month-independent supply elasticities is to have a rough estimate of acreage response to prices given the price information of the month(s) prior to planting time. We expect planting time prices to be better proxies for producers' expectations than just last year's prices since producers have a lot more knowledge at planting time. Additionally, we included monthly dummies in order to account for the effect of seasonality that may arise due to climatic and geographic conditions that may in turn affect the scale of cultivation in each specific planting month.

Table 2.4. Intra-annual global supply response estimates

Variable	**Wheat**	**Corn**	**Soybeans**	**Rice**$^{+}$
Acreage (t-12)	0.837***	0.842***	0.961***	0.821***
	(0.029)	(0.042)	(0.011)	(0.041)
Wheat price	0.068**	0.031	0.021	-0.014
	(0.027)	(0.020)	(0.032)	(0.013)
Corn price	0.021	0.114**	-0.086**	-0.010
	(0.028)	(0.055)	(0.036)	(0.014)
Soybean price	-0.057**	-0.015	0.144**	0.006
	(0.026)	(0.021)	(0.067)	(0.016)
Rice price	-0.023	-0.028**	0.011	0.007
	(0.017)	(0.013)	(0.024)	(0.008)
Fertilizer price	0.013	0.002	-0.032	-0.008
	(0.015)	(0.011)	(0.025)	(0.008)
Wheat price vol.	-0.894**	0.269	0.317	-0.377
	(0.425)	(0.279)	(0.602)	(0.240)
Corn price vol.	1.014**	0.286	0.057	-0.062
	(0.501)	(0.330)	(0.646)	(0.234)
Soybean price vol.	0.635*	-0.184	0.730	0.540**
	(0.336)	(0.331)	(0.583)	(0.234)
Rice price vol.	-0.151	0.072	-0.781**	0.189
	(0.306)	(0.276)	(0.366)	(0.154)
Trend	0	0.001	0.002**	0.001*
	(0.001)	(0.001)	(0.001)	(0.000)
R-squared	0.99	0.99	0.99	0.99
N		588		

Notes: Figures in parentheses are autocorrelation adjusted standard errors. Monthly dummies were also included for each crop regression and coefficients are available upon request. $^{+}$The rice price is the average price of the previous 12 months. *$P < 0.10$, **$P < 0.05$, ***$P < 0.01$.

Table 2.4 summarizes the monthly regression results. In this case, we assume farmers base their expectations on the spot prices during the pre-planting months.[14] Since including both first and second lagged prices for all the crops causes high multicollinearity problem, we alternatively include output prices of up to two-month lags for each cropland model. While the second lagged own price is not statistically significant for wheat and rice acreages, it is statistically important for corn and soybean acreage models. Thus, in order to avoid any simultaneity bias, which might result from imprecise crop calendar, we used the second lagged prices for the latter crop acreage models. The dependent own acreage variables are the values corresponding to the same month of the previous year.

In comparison with the annual model there are some interesting similarities. Analogously to the annual estimates, the monthly acreage responses are consistent with economic theory in the sense that area responds positively to own prices and negatively to competing crop prices. The fact that acreage, on global average, adjusts monthly to changes in international monthly prices prior to planting time attests that the prices preceding the planting period of these crops contain relevant information that the producers base their harvest time price expectations on. Aside from the wheat acreage where the coefficients are in the same order of magnitude, the monthly acreage responses to own crop prices are smaller than the annual responses. This suggests that producers base their price expectations not only on monthly prices but also on prices over a longer period before planting, as they already anticipate that the price immediately before planting time might change until harvesting. The results suggest that doubling of the respective own spot prices leads to – on a global average – acreage increases of between 7% for wheat, 11% for corn and 14% for soybeans in the short-run. Global monthly rice acreage is not responsive to own prices prevailing in the month before the start of the planting period. In addition to the responses to own crop prices, the monthly acreage specification findings reveal that higher crop prices result in lower land allocation for competing crop production. In particular, global wheat producers negatively respond to expected soybean prices whereas expectations of corn and rice crop prices are more important for global soybean and corn producers, respectively.

[14] Results from acreage models where we consider futures prices as proxy for farmers' price expectations are consistent with the reported results. These results are reported in the Table A3 in Appendix I.

In agreement with the annual crop acreage specification, price risk seems to be detrimental to wheat producers in the intra-annual acreage model. While higher fluctuations of the own crop price discourage producers from allocating more land to wheat production, this could be offset if prices of competing crops such as corn and soybeans also exhibit such fluctuations. The estimated lagged acreage planted variables were both statistically and economically relevant in determining current cultivations of all crops. With regard to the time trend, the global acreages of soybeans and rice have increasing trend, implying annual average growth rates of about 0.1% for rice and 0.2% for soybean acreages.

Seasonal supply elasticities

For the second intra-annual regression, we estimate the acreage response in typical planting months depending on prices in the preceding month. Similar to the monthly model above, we include individual crop area allocations in the same month of the previous year as additional explanatory variables. We present results for those months where cultivation of each crop is predominant in the global setting (see Figure 2.3 above). Table 2.5 presents the results for these selected months.

Table 2.5. Month-specific global elasticities for typical planting months

	Wheat			**Corn**		
Variable	**April**	**May**	**November**	**April**	**May**	**November**
Acreage (t-12)	0.506***	0.468***	0.822***	0.334***	0.346***	0.640***
	(0.097)	(0.106)	(0.092)	(0.118)	(0.126)	(0.096)
Wheat price	0.134***	0.303**	0.014	-0.044	-0.015	0.047
	(0.048)	(0.120)	(0.027)	(0.044)	(0.031)	(0.043)
Corn price	-0.05	-0.144	-0.018	0.111*	0.095**	-0.116*
	(0.045)	(0.110)	(0.028)	(0.060)	(0.044)	(0.060)
Soybean price	0.048	0.023	0.028	0.05	0.02	0.039
	(0.034)	(0.043)	(0.038)	(0.041)	(0.025)	(0.050)
Own price vol.	-0.627	-1.807	-0.252	-0.675	-0.082	0.937
	(0.468)	(1.089)	(0.301)	(0.758)	(0.422)	(0.822)
Fertilizer price	-0.023	-0.069**	-0.004	-0.006	-0.008	0.022
	(0.024)	(0.032)	(0.014)	(0.028)	(0.020)	(0.018)
Time trend	0.002**	0.005***	0.002	0.007***	0.008***	0
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.88	0.62	0.94	0.87	0.94	0.74
N	49					

Table 2.5. Continued.

	Soybeans			Rice		
Variable	**May**	**June**	**November**	**May**	**June**	**November**
Acreage (t-12)	0.792***	0.804***	0.923***	0.662***	0.680***	0.556***
	(0.104)	(0.056)	(0.043)	(0.063)	(0.063)	(0.110)
Wheat price	0.061	0.025	0.141	_	_	_
	(0.049)	(0.056)	(0.100)			
Corn price	-0.156**	-0.13	-0.068	_	_	_
	(0.063)	(0.078)	(0.157)			
Soybean price	0.178***	0.222***	0.013	_	_	_
	(0.057)	(0.054)	(0.148)			
Rice price	_	_	_	0.019*	0.022**	-0.01
				(0.010)	(0.010)	(0.020)
Own price vol.	0.158	-0.169	0.659	0.113	0.131	-0.213
	(0.728)	(0.700)	(0.750)	(0.179)	(0.165)	(0.292)
Fertilizer price	-0.039	-0.034	-0.005	0	-0.006	0
	(0.024)	(0.029)	(0.067)	(0.010)	(0.011)	(0.015)
Time trend	0.003	0.006***	0.004	0.001***	0.002***	0.002
	(0.002)	(0.002)	(0.004)	(0.000)	(0.000)	(0.001)
R-squared	0.94	0.98	0.99	0.92	0.94	0.82
N	49					

Notes: Figures in parentheses are robust standard errors. *P < 0.10, **P < 0.05, ***P < 0.01.

The short run own-price acreage elasticity for wheat ranges from 0.30 in May to nearly zero in November. Similarly, short-run own-price acreage elasticities range from 0.11 (corn in April), 0.22 (soybeans in June), and 0.02 (rice in June) to fairly price insensitive acreages in winter (November). In accordance with both the annual and the intra-annual results above, the month-specific cross-price acreage elasticity shows that the global soybean cultivation (in spring) competes for land with corn cultivation. It is also during the spring that the global wheat and soybean acreages respond to fertilizer prices. One explanation for this negative relationship could be that when fertilizer prices are high, acreage expansion is more profitable than increasing intensification. We also conducted a separate regression where we used average crude oil prices as additional explanatory variables (results are not reported here for reasons of brevity). The effect of crude oil prices is not clear since it implies higher production cost on the one hand and higher output prices due to higher demand for biofuel on the other hand. The results indicate that the latter effect outweighs in case of corn and soybeans where the global acreage of these crops positively respond to higher crude oil prices.

The estimated coefficients of the lagged area were both statistically and economically relevant in determining the acreage at any particular planting month of all crops. As opposed to the acreage responses to output and input prices, the lagged own acreage coefficients are relatively larger during the winter months. This may affirm the already implied relative rigidity of acreage allocation during the winter. Similar to the above results, the estimated coefficients indicate that global soybean acreage has the largest producers' inertia that may reflect adjustment costs in crop rotation and crop specific land and/or soil quality requirements. However, the coefficients of the lagged dependent variables might also reflect unobservable dynamic factors and interpretation should be made with caution (Hausman, 2012).

This seasonally variable global acreage response may be partly explained by the lower availability of land during spring as it is the dominant planting season for all of these four crops although less so for wheat. The differences of the coefficients across the months also reflect differences across the countries where sowing takes place in the respective months and captures characteristics such as global market integration or domestic institutions and government policy interventions. The time trend estimates show that more and more land has been allocated for these crops during the spring season. The results demonstrate that the global acreage of all these crops has been consistently growing at an annual rate of between 0.1% and 0.8% during spring. On the other hand, neither of the crop acreages shows any significant time trend during the winter.

In summary, our empirical results align with previous work in this topic. Table 2.6 below gives a summary of acreage elasticities for selected countries estimated by the Food and Agricultural Policy Research Institute (FAPRI) and other literature. With the exception of the elasticity reported by Roberts and Schlenker (2009), elasticties are at national or sub-national levels. While the supply elasticity from Roberts and Schlenker (2009) is at a global level and straightforward to compare with the estimated elasticties of this study, it is aggregated for all the four crops in terms of their caloric content. Apart from rice acreage elasticties that are smaller in this study, our estimated elasticities are mostly comparable with existing elasticity estimates at the national level. This has implications for whether our estimates serve as complements to or substitutes for micro and national level supply models and as verifications of whether involved household and farm level estimations add up to patterns that are apparent in the aggregate global data.

Table 2.6. Summary of existing own price acreage elasticities

Countries	Wheat	Corn	Soybeans	Rice
Africa				
Egypt	0.25	0.09	0.03	0.16
South Africa	0.09	0.28	0.03	0.03
Asia				
China	0.09	0.13	0.45	0.16
India	0.29	0.21	0.36	0.11
Pakistan	0.23	0.28	0.29	0.29
South America				
Argentina	0.41	0.7	0.32	0.24
Brazil	0.43	0.42	0.34	0.07
Middle East				
Turkey	0.2	0.14		0.47
Iran	0.08	0.01	0.01	0.01
Europe				
EU	0.12	0.08	0.19	0.24
Russian Federation	0.19	0.31	–	–
North America				
Canada	0.39	0.18	0.32	–
United States	0.25	0.17	0.3	0.35
Australia				
Australia	0.33	0.23		0.17
Weighted average (weighted by area share)	***0.18***	***0.14***	***0.31***	***0.07***
Roberts and Schlenker (2009), Global		0.11		
Roberts and Schlenker (2013), Global	0.10	0.27	0.55	0.03
This study, Annual model	*0.09*	*0.18*	*0.37*	*0.02*
This study, Intra-annual model	*0.07*	*0.11*	*0.14*	*0.01*
This study, Annual month-specific model	*0.30*	*0.10*	*0.22*	*0.02*

Source: Food and Agricultural Policy Research Institute (FAPRI).[15]

Note: Since FAPRI does only report rice acreage elasticties for the United States, we took elasticties from Lin and Dimuskes (2007) for the other crops. We also took average acreage elasticties for other Africa for non-reported elasticties for Egypt and South Africa. Price elasticities for individual countries refer acreage responses to domestic (producer) prices while global price elasticities of this study refer to responses to world market prices.

[15] http://www.fapri.iastate.edu/tools/elasticity.aspx

2.6. Conclusions

In recent years, global crop production has faced a series of emerging issues and showed noticeable variations in acreage. Factors such as ongoing developments in bio-technology, fluctuations in corn and soybean prices due to the rising demand for ethanol and changes in production costs affect producers' acreage allocation decisions. These changes have huge implications for the global food supply as well as for the agribusiness sector such as input supply industries. To this end, a recent study showed that land use changes, as a result of expansion of biofuels, significantly decreases global food supply mainly in developing countries (Timilsina et al., 2012).

This study is the first of its kind in estimating annual and intra-annual acreage responses at a global scale. We have used country-specific crop calendar in order to apportion annual acreage values into respective planting months and to choose the most likely output prices that shape producers' price expectations. This enables us to investigate how crop acreages in one part of the world are affected by harvest changes in the other part of the world. Global acreage responds to monthly as well as to annual price changes, the latter being slightly stronger. Generally, corn and soybean acreages are more responsive to prices with annual short-run own-price elasticities of 0.18 and 0.37, respectively, than wheat (0.09) and rice (0.02). Land for rice cultivation requires capital investment (canals, sluices etc.) to ensure flooding at the time of planting. These investments are long-term decisions. Short run price responses are therefore inevitably low. In general, the low acreage supply elasticities may be indicative of the need for productivity improvements to meet (growing) demand, as area expansion is economically and environmentally limited.

Acreage response to price changes, however, leads to further acreage response through the auto-regressive term in the following period. The long-run acreage responses, measured as the area response for an infinite time horizon due to a permanent shift of prices, are, in equilibrium, larger than the short-run responses. In the annual acreage model, for instance, while long-run price elasticity of wheat acreage is about twice larger than the short-run elasticity, those of soybeans and rice are more than three times larger than their respective short-run elasticity estimates. The long-run price elasticity of corn acreage is also slightly larger than the short-run value. Thus, we might observe a higher acreage increase in the long-term due to global price increases than what the short-term elasticities suggest.[16]

Although the estimated short-run global acreage responses to price changes are generally small, they vary across crops and exhibit seasonal variability. Our disaggregation from annual to monthly acreage data allows us to further study the intra-annual acreage responses to prices and other factors. The monthly acreage response model resulted in month-independent price elasticities that are of comparable magnitude with the annual price elasticities. However, the seasonal month-specific price elasticities reveal that global acreages respond stronger to price changes in some specific months than in others. More specifically, the area planted during spring is more price sensitive than area planted in winter owing partly to greater land competition during the spring season. This may also reflect other country-specific reasons including national policies that limit the flexibility of crop acreage adjustments.

Results from this study indicate a negative impact from price uncertainty, measured by output price volatility, on aggregate supply response for the major global field crops. The annual acreage model results show that own output price volatility introduces risks that affect the investment decisions of a risk-averse agent and ultimately results in a lower acreage allocation of the respective crop. Furthermore, both the own and competing crop price fluctuations are statistically significant and economically relevant to global wheat acreage allocation in the intra-annual model. The results indicate that, on average, global wheat acreage declines in response to higher own price volatility. It is a well-known finding in economic theory that price uncertainty is a disincentive to agricultural producers under the underlying risk aversion assumption and where insurance markets are poorly operating (Sandmo, 1971). The findings in this study support that this behavioral assumption of risk-aversion is likely to hold for the majority of the wheat, corn, soybeans and rice producers in the world. This is relevant for policy makers suggesting that managing output price volatility could lead to an expansion of agricultural land and hence crop production.

[16] The Long run and short run elasticities are reported in Table A4 in the Appendix I.

3. A dynamic panel data analysis of production, area and yield responses

Abstract[*]

This chapter estimates global supply response for the key agricultural commodities wheat, rice, corn, and soybeans, employing a newly developed multi-country, crop-calendar–specific, seasonally disaggregated model with price changes and price volatility applied accordingly. The findings reveal that, although higher output prices serve as an incentive to improve global crop supply as expected, output price volatility acts as a disincentive. Depending on the crop, the results show that own price supply elasticities range from about 0.05 to 0.35. Output price volatility, however, has negative correlations with crop supply, implying that farmers shift land, other inputs, and yield-improving investments to crops with less volatile prices. Simulating the impact of price dynamics since 2006, we find that price risk has reduced the production response of wheat in particular—and to a lesser extent, rice—thus dampening price incentive effects. Own-price volatility tends to dampen yield by about 1% to 2% for the crops under consideration.

Key words: food prices, price volatility, global supply response, staple food commodities

***JEL codes*:** O11, O13, Q11, Q13, Q18, Q24

[*]Most of the material in this chapter is drawn from our publication in the *American Journal of Agricultural Economics*: Haile, M. G., Kalkuhl, M. and von Braun, J. (2015), http://ajae.oxfordjournals.org/content/early/2015/04/15/ajae.aav013.abstract.

3.1. Introduction

After about three decades of low and relatively stable prices for staple food commodities, the world has experienced a surge in the prices of many staple food commodities since 2005. Such high prices are typically expected to bring about a supply response in which producers allocate more land to the agricultural sector and increase investment to improve yield growth (OECD, 2008). Higher prices were, however, accompanied by higher volatility (Gilbert & Morgan, 2010). Price volatility introduces output price risk, which has detrimental implications for producers' resource allocation and investment decisions (Moschini & Hennessy, 2001; Sandmo, 1971). Because agricultural producers in many developing countries are often unable to deal with (Binswanger & Rosenzweig, 1986) and are unprotected from (Miranda & Helmberger, 1988) the consequences of price volatility, they are exposed to the effects of international agricultural market price instability to the extent it is transmitted to local markets. Given this backdrop, this study analyzes the supply responsiveness of key world staple food commodities—namely, wheat, corn, soybeans, and rice—to changes in output prices and volatility. Understanding how global food commodity producers allocate cropland and how their decisions about crop production are affected by changes in price levels and volatility is fundamental for designing policies related to agricultural growth and food supply.

The literature on estimation of supply response to prices has a long history in agricultural economics (Houck & Ryan, 1972; Lee & Helmberger, 1985; Nerlove, 1956). Nevertheless, there are various reasons to reconsider the research on supply response. The majority of the previous empirical literature is concentrated on a few countries, lacking global linkages. Also, the effect of price levels and price volatility has usually been considered a micro-level problem limited to the producer. Now, however, several factors such as foreign direct investment in agriculture make global and country-level agricultural production sensitive to price levels and volatility, as is the case at the individual producer level. Another reason for renewed research interest in the topic is the growing demand for biofuels and the financialization of agricultural commodities, which are suspected to have contributed to the high and volatile food prices that have in turn affected the global food supply (Gilbert & Pfuderer, 2014; Tadesse et al., 2014).

Furthermore, existing econometric analyses focus on supply responses to domestic prices. In contrast, this study investigates the supply response of the key world staples to international market prices. In doing so, the chapter makes the following major contributions: (1) It provides updated short- and long-term supply elasticities that indicate how major agricultural commodity producers have responded to the recent increase in global food prices and volatility. This reveals to what extent the global agricultural system is responding to emerging global food scarcities. (2) It addresses whether the recent increase in prices and price volatility is an opportunity or a challenge to agricultural producers and to the agriculture sector in general. (3) Given some empirical evidence suggesting that the largest share of the supply response to output price, in the short run, is through acreage adjustments (e.g. Roberts & Schlenker, 2009), both acreage and yield responses are estimated to contest or affirm this finding. (4) It uses simulation analyses to assess the overall impacts of recent agricultural commodity price dynamics on the supply of key staple crops.

The rest of the chapter is organized as follows: The next section presents a brief overview of global production, acreage, and yield. The sections that follow provide the modelling framework and newly constructed data used for the empirical analysis and then present and discuss the econometric and simulation results. The last section concludes.

3.2. Production, Acreage, and Yield: An Overview

Agricultural productivity and competition for land are the major drivers of global food production and farming in the future (Smith et al., 2010). Whereas total cropland constituted less than a tenth of the global land cover in the 18th century (Beddow et al., 2010), about a third of global land area is devoted to agricultural use today (Hertel, 2011). Although there is little room for extensification (bringing more land under crop cultivation) in South and East Asia, the Middle East, North Africa, and many advanced economies, extensification may have substantial potential to increase crop production in other regions such as Sub-Saharan Africa and Latin America (Bruinsma, 2003). The recent rise in agricultural commodity prices has also resulted in more competition for agricultural land and raising land prices. For instance, there have been large foreign agricultural investments in many developing countries, primarily focusing on growing high-demand crops including corn, soybeans, wheat, rice, and other biofuel crops (von Braun & Meinzen-Dick, 2009). Rising agricultural commodity prices should also be incentives for larger agricultural investments in yield-improving technologies.

The global dynamics depicted in Figure 1.2 reflects the changes in the major producer countries of each crop. Table 3.1 shows the ten-year average and percentage change in production, acreage, and yield between the decades 1961–1970 and 2001–2010. In line with the global changes already described, aggregate production in the top six cultivating countries increased most for soybeans, followed by corn. Production and yields of all four crops were higher in all six top producer countries in 2001–2010 than they were in the 1960s. Large expansions in soybean acreage took place in all of these countries except China. China has increased its soybean imports, a situation that has been at least partly responsible for the strong expansion in soybean acreage in the Latin American countries. The three largest soybean producer countries in Latin America—Brazil, Argentina, and Paraguay—accounted for close to 45% of the global soybean acreage in 2010, up from merely half a percent in 1961. Similarly, area under wheat and rice cultivation has increased for all countries except China. The area under corn cultivation has risen for all countries except Mexico. India experienced expansion in sown acreage for all four crops during this period. In addition, India’s share of global acreage for these crops was higher in 2010 than in 1961, except for a slight decline in the case of rice. Other Asian countries including Indonesia, Thailand, Myanmar, and Viet Nam increased their share of global rice acreage. No African country is among the top six cultivating countries of any of these four crops.

Although production, acreage, and yield of all four crops have increased during the past five decades, Figure 1.2 shows that the changes have not always been smooth upward trends. This chapter examines how the supplies of the four staple food commodities have responded to international price levels and price volatility. Cross-country panel data are used for panel econometrics in order to test hypotheses on the scale and determinants of crop supply responses to price levels and price volatility.

Table 3.1. Production, area, and yield for selected crops of the six largest cultivating Countries, 1961–1970 and 2001–2010

	Production (million MT)			Area (million ha)			Yield (MT/ha)		
Crop/country	*1961–1970*	*2001–2010*	*% Δ*	*1961–1970*	*2001–2010*	*% Δ*	*1961–1970*	*2001–2010*	*% Δ*
Wheat									
India	13	73	452	14	27	92	0.9	2.7	191
EU	57	133	132	25	26	2	2.3	5.1	126
China	23	102	337	25	23	-6	0.9	4.4	364
USA	36	57	58	20	20	1	1.8	2.8	56
Russian Federation[a]	36	49	35	22	24	6	1.2	2.0	73
Australia	9	20	109	8	13	63	1.2	1.5	27
Top six total	*175*	*434*	*147*	*114*	*133*	*16*	*1.4*	*3.1*	*123*
Corn									
USA	104	286	174	23	31	33	4.5	9.3	106
China	25	143	468	16	28	77	1.6	5.2	222
Brazil	11	46	304	9	13	49	1.3	3.6	171
India	5	16	203	5	8	49	1.0	2.1	102
Mexico	8	21	164	7	7	-1	1.1	3.0	169
EU	23	59	160	8	9	6	2.7	6.6	147
Top six total	*177*	*573*	*223*	*68*	*95*	*39*	*2.1*	*5.0*	*143*
Soybeans									
USA	24	81	236	14	30	109	1.7	2.7	62
Brazil	1	53	8,327	1	20	3,427	1.1	2.6	143
Argentina	0.02	38	209,107	0.02	14	87,268	1.1	2.6	140
India	0.01	9	87,672	0.02	8	36,069	0.4	1.1	139
China	8	15	106	9	9	2	0.8	1.7	99
Paraguay	0.02	5	23,144	0.01	2	20,080	2.1	2.3	10
Top six total	*32*	*201*	*521*	*24*	*83*	*251*	*1.2*	*2.2*	*80*
Rice									
India	55	135	147	36	43	19	1.5	3.1	107
China	88	184	109	30	29	-4	2.9	6.3	119
Indonesia	14	57	294	7	12	62	1.9	4.7	145
Bangladesh	16	42	164	9	11	16	1.7	3.8	128
Thailand	12	31	153	7	10	58	1.8	2.9	61
Myanmar	8	28	261	5	7	56	1.6	3.8	130
Top six total	*193*	*476*	*147*	*95*	*113*	*20*	*1.9*	*4.1*	*115*

Source: Data are from FAO (2012) and national sources.

Notes: The production and area figures are annual averages for the respective periods and crops of the top six largest cultivating (in terms of area) countries as of 2010. Yield in the "Top six total" rows refers to the average yield of the six countries. EU refers to the 27 countries that were members of the European Union as of 2010.

[a]In the case of the Russian Federation, the annual average for 1992–2000 is used for the 1961–1970 column.

3.3. Review of related literature

This study builds on the extensive agricultural economics literature on the estimation of agricultural supply response. Elasticities from a supply response model refer to the speed and size of adjustments in desired output to expected output prices. Neither the desired output nor the expected price is observable, however. The empirical literature employs different types of proxies for these variables, which could affect the results obtained. We attempt to briefly revise the literature with respect to the alternative proxies of these two variables.

In terms of the proxy for expected output prices, the literature does not provide unambiguous evidence regarding which expectation model to use for empirical agricultural supply response estimation (Nerlove & Bessler, 2001; Shideed & White, 1989). The widely applied expectation formation hypotheses in the supply response literature include naïve expectation (Ezekiel, 1938), where expected prices are assumed to be equal to the latest observed prices; adaptive expectation (Nerlove, 1958), where farmers are assumed to revise their expectations depending on past errors; and rational expectation (Muth, 1961), which assumes that expectations are consistent with the underlying market structure and that economic agents make efficient use of all available information. Other research has focused on modelling supply response models using a quasi-rational price expectation (Holt & McKenzie, 2003), which is consistent with price prediction from a reduced-form dynamic regression equation. Futures prices are also used as proxy for price expectations (Gardner, 1976). The naïve and adaptive expectation hypothesis are criticized to be backward-looking (Nickell, 1985); in other words, they ignore that the dynamics of price expectations by decision-makers can influence prices in the future. Although forward looking, the rational expectation hypothesis is criticized as it implies that economic agents make efficient use of all available information, which may not be the case when some information is costly or difficult to process (Chavas, 2000). Additionally, the rational expectation is not supported in some experimental and survey datasets (Nelson & Bessler, 1992; Nerlove & Schuermann, 1995). The applicability of futures price as a proxy is also dubious in supply analyses in countries where farmers are neither able to make any futures transactions nor have access to information from exchange markets. Moreover, some empirical evidence shows that heterogeneous expectations coexist among agricultural producers simultaneously (Chavas, 2000).

Following Nerlove (1958) several empirical supply response models employ the adaptive expectation hypothesis and its variants. Askari & Cummings (1977) and later Nerlove & Bessler (2001) provide a thorough review of such literature; however, Yu et al. (2012); Vitale et al. (2009), and de Menezes and Piketty (2012) can be mentioned as recent examples. While Aradhyul & Holt (Aradhyula & Holt, 1989) employ the rational expectation hypothesis to investigate broiler supply in the US, Eckstein (1938) and Lansink (Lansink, 1999) employ this hypothesis to estimate crop acreage elasticities using aggregate agricultural data and farm-level data respectively. Moreover, other empirical applications show the relevance of the quasi-rational expectation approach in their supply models (Holt & McKenzie, 2003; Nerlove & Fornari, 1998). Last but not least, including Gardner (1976) himself, Lin and Dsimukse (2007), Liang et al. (2011) and Hausman (2012) are a few of the studies that use harvest time futures prices as proxy for farmers' price expectations at planting season.

The empirical agricultural supply response literature often uses acreage, yield or production as a proxy for desired output supply. Several studies prefer to use acreage to production in modelling output supply response (Coyle, 1993; Haile et al., 2014) since acreage, unlike observed output, is not influenced by external shocks that occur after planting. However, acreage elasticities may only serve as a lower bound for the total supply elasticity (Rao, 1989), as the latter depends also on yield changes to prices. Accordingly, several studies estimate both acreage and yield responses to prices (Mythili, 2008; Weersink et al., 2010; Yu et al., 2012). When there is little interest in whether supply response to output prices occurs via acreage or yield, total observed production is another proxy used to estimate output supply response in the literature (Coyle, 1999). Because "external" weather and pest shocks —that usually happen after farmers make their production decisions and that are hardly predictable for farmers to take them into account in their production decisions — influence this proxy, the estimated supply response may not reflect the actual response of farmers to prices. There is, however, another proxy that is being used in recent studies— total caloric production, which is the sum of the caloric value of specific crops (Roberts & Schlenker, 2009, 2013). This proxy implicitly assumes that the crops in the caloric aggregate are perfectly substitutable, which is less plausible as it assumes identical land and other input requirements for each crop. This ignores the possibility of producers to switch across crops as a result of changes in relative prices, which is supported by recent study that shows acreage expansion of higher demand crops, such as corn, by shifting out land from lower demand crops (Abbott et al., 2011; Goodwin et al., 2012). Such aggregation excludes inter-crop acreage and other input shifts, which, by definition, implies that aggregate output elasticities are likely to be smaller than crop-specific elasticites. This conforms to the statistically significant cross-price elasticities of crop acreage findings of several studies. Hendricks et al. (2014), for instance, conclude that most of the acreage response to price of corn and soybeans in the US occurs through substitution rather than through area expansion. Aggregation of crops also conceals any implications for and effects of crop-specific policies with respect to changing intra-commodity price relations.

On the other hand, output supply can be estimated at plot or farm-level, where farm size, soil-quality and other farm characteristics that may influence supply response can be controlled for; at household level, which enables better understanding of supply behavior of farmers; or at larger aggregation scopes such as at national, regional, or global levels, which have methodological limitations to capture the effects of contextual factors but that still enable to sufficiently measure supply responsiveness. Yet, estimation of aggregate agricultural supply response to changing price incentives is essential as it has crucial implications for economic growth and poverty alleviation of economies with a sizable share of the agricultural sector in their national income. While there are several farm- and micro-level studies (e.g. Lansink, 1999; Vitale et al., 2009; Yu et al., 2012) and good number of studies at national level (e.g. Barr et al., 2009; de Menezes & Piketty, 2012), global level studies are few. Nevertheless, cross-country analyses using a certain group of countries are conducted to determine the role of prices on agricultural supply. Peterson (1979), for instance, finds that agricultural supply in developing countries fairly respond to crop prices (estimated long run elasticities range between 1.25–1.66). Using a sample of 58 countries from the period 1969–1978, Binswanger et al. (1987), on the other hand, find that agricultural supply responds weakly to price incentives but strongly to non-price factors. More recent cross-country study by Subervie (2008) based on a sample of 25 developing countries between 1961 and 2002 finds a rather small but statistically significant aggregate supply elasticity of 0.04. Findings from Imai et al. (2011), which use data from a panel of ten Asian countries, and other crop-disaggregated studies that find much larger supply elasticities hint that such aggregation of crops could result in the small supply elasticities. The other scope of aggregation is when supply is aggregated over all countries and crops. Two similar studies by Roberts and Schlenker (2009, 2013) estimate the caloric aggregated world supply and demand of staple crops— corn, wheat, soybeans, and rice—and find supply elasticity in the range of 0.055–0.116. They use lagged weather shocks, approximated by deviations of yield from trend, to identify the supply elasticity of agricultural commodities. Hendricks et al. (2014) replicate Roberts and Schlenker's analysis and found little difference between their estimates that control for the realized yield shock and the estimates by Roberts and Schlenker that use weather shocks in the previous year as an instrument for potentially endogenous expected prices. These authors also suggest that the use of planted acreage as dependent variable can reduce this endogeneity bias in the supply elasticity estimates. Along the lines of this suggestion, Haile et al. (2014) aggregate acreage of all countries to estimate crop-specific world supply elasticties that range between 0.03 for rice and 0.34 for soybeans.

The present chapter subtly differs from the literature discussed above, in terms of both the level of aggregation employed for the dependent variables and the proxy used for expected prices. Besides using all crop acreage, yield and production as alternative proxies for the desired output supply, these variables are aggregated at the world level for each crop. Nevertheless, the aggregation retains the panel feature of the data, which enables us to control heterogeneities across countries. For example, we make use of the country and crop specific planting and harvesting seasons to assign the relevant proxy for price expectation in each country and for each crop. This leads us to the second point on how our proxy for expected prices differs from that used in the literature. We use planting season world price as proxy for farmers' anticipated prices in each country, in other words, we estimate crop supply response to changes in world prices rather than to specific domestic prices. Thus, unlike the commonly understood agricultural supply response, which estimates how output supply responds to changes in prices that producers face, we estimate production, area and yield responses to changes in international prices. These two supply response estimates are identical under the assumption of complete transmission of international prices to domestic producer prices. However, they could be different in case of incomplete price transmission – an argument which is supported by the literature (e.g. Kalkuhl, 2014). Finally, with the exception of Subervie (2008), none of the cross-country panel studies discussed above and, to our knowledge, no worldwide aggregated supply response study except Haile et al. (2014) has accounted for price volatility (price risk) in the respective supply models.

3.4. Conceptual Framework

The supply response literature has gone through several important empirical and theoretical modifications, out of which two major frameworks have been developed. The first approach is the Nerlovian partial adjustment model, which allows for analyzing both the speed and the level of adjustment from actual toward desired output. The second is the supply function approach, derived from the profit-maximizing framework. This second approach requires detailed input prices and simultaneous estimation of input demand and output supply equations. However, input markets—in particular land and labor markets—are either missing or imperfect in many countries. Moreover, our main interest lies in the output supply function. Thus, the econometric approach of the present study is in line with the partial adjustment framework, enhanced with dynamic (including intra- annual) response, alternative price expectation assumptions, and the introduction of price-risk variables.

There has been a wide variety of applications of the Nerlovian model with modifications of the original framework. Modifications have included alternative expectation assumptions such as the use of futures prices as additional information in price expectation formation (Gardner, 1976), expected net returns rather than prices alone (Chavas & Holt, 1990; Davison & Crowder, 1991), and output/land value rather than prices or returns (Bridges & Tenkorang, 2009). Risk variables have also been included to capture the behavioral aspects of farmers' decisions (Liang et al., 2011; Lin & Dismukes, 2007). Furthermore, in earlier studies time-series data were often used to capture the dynamics of agricultural production, and more recently econometric developments have allowed for the use of panel data.

Models of the supply response of a crop can be formulated in terms of output (Q), area (A), or yield (Y) response. For instance, the desired output of a certain crop in period *t* is a function of expected output prices and a number of other exogenous factors (Braulke, 1982):

$$Q_t^d = \beta_1 + \beta_2 p_t^e + \beta_3 Z_t + \varepsilon_t \qquad (3.1)$$

where Q^d is the desired output in period t; $p^e$is a vector of the expected price of the crop under consideration and of other competing crops; Z is a set of other exogenous variables including fixed and variable input prices, climate variables, and technological change; ε_t accounts for unobserved random factors affecting crop production with zero expected mean; and β_i are the parameters to be estimated. Usually output (determined by area and yield) adjustments are delayed for one or two agricultural production cycles because of lack of resources. To account for such time lags in agricultural supply response, it is important to apply a dynamic approach. Supply response is usually a two-stage process. Because harvest-time prices are not realized during the time of planting, producers, in the first stage, make acreage allocation decisions conditional on expected prices. As in the production equation above, the desired area to be cultivated for a certain crop at time t is determined by expected own and competing crop prices and other non-price factors:

$$A_t^d = \alpha_1 + \alpha_2 p_t^e + \alpha_3 Z_t + \varepsilon_t \tag{3.2}$$

Given the acreage allocation for each crop, farmers then determine crop yield based on other inputs and climate conditions. During the growing period, they may make revisions to their production practices by adjusting input quantity, input quality, and crop protection. Hence, the desired yield of each crop is defined similarly to equations (3.1) and (3.2) except that the output price vector includes only the crop's own price.

3.5. Data

The econometric model relies on a comprehensive database covering the period 1961–2010. The empirical model uses global and country-level data in order to estimate global production, acreage, and yield responses for the world's key staple crops. While data on planted acreage are obtained from several relevant national statistical sources,[17] harvested acreage, production, and yield for all countries are obtained from the Food and Agriculture Organization of the United Nations (FAO). Area harvested serves as a proxy for planted area if data on the latter are not available from the relevant national agricultural statistics. International spot market output prices as well as different types of fertilizer prices and price indices are obtained from the World Bank's commodity price database. All commodity futures prices are from the Bloomberg database. Table 3.2 reports the 31 countries or regions included in this study, and the rest of the world is aggregated.

[17] Data sources are available in Appendix I, Table A9.

A producer may choose to cultivate different crops at planting time (Just & Pope, 2001). Therefore, it is worthwhile to consider price, price risk, and other information available to the farmer during the planting season. Accordingly, we use crop calendar information to identify the major planting seasons of each country in order to construct country-specific spot and futures prices, measures of price risk and yield shocks, and input prices.[18]

Table 3.2. Study countries and regions

Asia	***Africa***	***South America***	***Europe***
Bangladesh	Egypt	Argentina	EU-27
Cambodia	Ethiopia	Brazil	Russian Federation
China	Nigeria	Mexico	Ukraine
India	South Africa	Paraguay	
Indonesia		Uruguay	
Japan			
Kazakhstan			
Myanmar	***Middle East***	***North America***	***Australia***
Pakistan	Iran	Canada	Australia
Philippines	Turkey	USA	
Sri Lanka			***Other***
Thailand			Rest of the world
Uzbekistan			(ROW)
Viet Nam			

Notes: While data on production and area are pooled across the 27 EU member countries and across all the remaining countries for the "Rest of the world", data on yield are averages of all the countries within each group. Post-1991 data are applicable for the former Soviet Union countries.

Because actual prices are not realized during planting, we model farmers' price expectations using the relevant spot and futures world price information available during planting. Since they contain more recent price information for farmers, own and competing crop spot prices observed in the month before the start of planting are used in the empirical model. Alternatively, harvest-time futures prices quoted in the months prior to planting are used. The use of these two price series to formulate producers' price expectations makes our supply response models adaptive as well as forward-looking. Because the planting pattern varies across countries and crops, both the

[18] The crop calendar for emerging and developing countries is obtained from the Global Information and Early Warning System (GIEWS) of the FAO, and the crop calendar for the advanced economies is from the Office of the Chief Economist (OCE) of the US Department of Agriculture (USDA). Tables A5-A8 in Appendix I present the crop calendar information for several countries.

futures and spot prices of each crop are country-specific. For countries in the rest of the world (ROW), we use annual average spot and generic futures prices.[19]

The level of transmission of international to national prices can of course vary among countries. By using international instead of local prices, we implicitly assume that international price change is a proxy for domestic producer price change. Comparisons of the global and national supply response elasticities point to the fact that price transmission from world to domestic prices is in some countries imperfect or absent. Consequently, producers' response to international price changes and volatility—that is, the focus of this study—should be expected to be low. Empirical evidence, however, shows that world prices are a significant source of variation in domestic prices, even when countries are poorly integrated with the global agricultural market (Mundlak & Larson, 1992). Recent empirical literature also shows that domestic markets are integrated to world markets mostly through adjustment of domestic prices to deviations from the long-run domestic-world price relationship (Baquedano & Liefert, 2014; Kalkuhl, 2014).

We include yield shocks calculated as deviations from country and crop-specific trends in our empirical supply models. Our presumption is that these deviations from the respective yield trends, which may be a result of weather shocks, pest infestations, or other factors, could serve as proxy for producers' yield expectations. Following Roberts and Schlenker (2009), the yield shocks are the jackknifed residuals from separate yield-on-trend regressions for each crop in each country. A positive deviation entails good yield expectations, implying a positive effect on crop supply. For countries in the ROW, we pool the crop yields across the remaining countries to generate yield shocks for each crop.

Own and cross volatility of international spot prices are used to capture output price risk. For price volatility we use the standard deviation of the log returns (that is, first differences instead of levels of log prices) in order to use the de-trended price series. The price-risk measures show country-specific output price variability in the 12 months preceding the start of the planting season of each crop in each country. Table 3.3 presents international price volatility along with the respective average real prices for all four crops. The volatility of world prices of selected

[19] Countries with a global acreage share of less than half a percent are grouped in the rest of the world (ROW) category.

crops, as measured by the moving standard deviation of monthly logarithmic prices, was higher in the recent decade relative to earlier periods, although not as high as in the 1970s.

Table 3.3. International price volatility and levels for wheat, corn, soybeans, and rice

	Price volatility				Price level			
Period	Wheat	Corn	Soybeans	Rice	Wheat	Corn	Soybeans	Rice
1961–1970	0.06	0.07	0.08	0.10	258	220	467	594
1971–1980	0.16	0.12	0.18	0.19	267	210	502	598
1981–1990	0.09	0.13	0.12	0.13	182	140	320	331
1991–2000	0.13	0.13	0.08	0.14	149	113	256	285
2001–2010	*0.15*	*0.14*	*0.15*	*0.13*	*191*	*133*	*323*	*328*
2001–2005	*0.11*	*0.11*	*0.13*	*0.09*	*160*	*111*	*273*	*236*
2006–2011	*0.21*	*0.19*	*0.16*	*0.16*	*227*	*169*	*384*	*423*

Notes: Price volatility is measured by the standard deviation of logarithmic monthly prices using World Bank international prices. Prices are in real 2005 US dollars per metric ton. The figures in each row refer to average values of the annualized volatilities and prices over the respective decade.

Fertilizer price indices are used as proxies for production costs in the present study. Given the weights used by the World Bank, the fertilizer price index contains the prices of natural phosphate rock, phosphate, potassium, and nitrogenous fertilizers. The fertilizer price indices are also crop- and country-specific depending on the planting pattern of each crop in each country. The fertilizer price index in the month prior to the start of planting is used.

3.6. Econometric Model

Given the above theoretical model and assuming there are *K* countries observed over *T* periods, the supply functions of the four crops can be specified most generally as

$$Q_{ikt} = \pi_i Q_{ik,t-1} + \sum_{j=1}^{4} \alpha_{ij} p_{jk,t_k} + \sum_{j=1}^{4} \varphi_{ij} vol(p)_{jk,t_k} + \lambda_{i1} w_{ik,t_k} + \lambda_{i2} YS_{ik,t_k} + \mu_{it} + \eta_{ik} + u_{ikt} \tag{3.3}$$

where Q_i denotes the total production (or area under cultivation) of crop i (1 = wheat, 2 = corn, 3 = soybeans, and 4 = rice), p denotes a vector of either spot or futures prices that are used to proxy expected own and competing crop prices at planting time, $vol(p)$ is a vector of the volatility measures for own and competing crop prices, w refers to prices of variable inputs (such as fertilizer), YS refers to a yield shock for each crop, μ captures time dummies to account for some structural changes or national policy changes, η denotes country-fixed effects to control for all time-invariant heterogeneities across countries, and u denotes the idiosyncratic shock. π, α, φ, and λ are parameters to be estimated. The subscript k denotes the country: this implies that the lag lengths of the relevant futures and spot price, output price volatility, input price, and yield shock variables are country-specific. As mentioned, the seasonality of agricultural cultivation in different countries enables us to construct international prices that are country-specific variables at the seasonally appropriate time in terms of each country's crop calendar. This approach is more precise than assuming that all countries face the same yearly output price. This is particularly important given that planting decisions in the early months of the calendar year (or marketing year) in some countries affect the annually averaged price and would cause an endogeneity problem in any global supply response model that uses annual data. Likewise, if planting decisions take place later in the calendar or marketing year, an average annual price will contain past prices that dilute the information signal that more recent planting-time prices could convey.[20] Taking the lagged annual average price is not a good remedy because producers adjust their price expectations with more recent information (Just & Pope, 2001).

As described in the conceptual model section, the yield equation is specified similarly to equation (3.3) except that the output price and price volatility vectors do not include price and volatility of competing crops. There is a subtle difference between the yield deviation measures used in the acreage and yield response models in order to proxy yield expectations. Whereas they are derived from the harvest period prior to planting in the acreage response models, they are derived from the harvest of the previous year in the yield response models. Accordingly, the deviations in the yield response models are lagged whereas they need not be lagged in the acreage response models if the prior harvest was in the year of planting. We therefore exclude these variables from the regressions of the production and yield response functions because they are by definition correlated with the respective lagged dependent variables.[21] All quantity, output, and input price variables (except for price volatilities, which are rates) are specified as logarithms in the econometric models. Hence, the estimated coefficients can be interpreted as short-run elasticities.

[20] See Chapter 2 for global intra-annual planting and harvesting patterns.
[21] The yield shock variables are not statistically significant in the acreage response models, and we omit them from the final regression.

Applying ordinary least squares (OLS) estimation to a dynamic panel data regression model such as in equation (3.3) above results in a dynamic panel bias because of the correlation of the lagged dependent variable with the country-fixed effects (Nickell, 1981). Since current acreage is a function of the fixed effects (η_k), it is obvious that lagged acreage is also a function of these country-fixed effects. This violates the strict exogeneity assumption, and hence the OLS estimator is biased and inconsistent. An intuitive solution to this problem is to transform the data and remove the fixed effects. However, under the within-group transformation, the lagged dependent variable remains correlated with the error term, and therefore the fixed-effect estimator is biased and inconsistent. While the correlation between the lagged dependent variable and the error term is positive in the simple OLS regression, the estimated coefficient of the lagged dependent variable is biased downward in the case of the fixed effects estimator (Roodman, 2009a, 2009b).

Therefore we need an estimator that gives an estimate of the true parameter that lies in the range of the OLS and the fixed effects estimate for the coefficient on the lagged dependent variable. Anderson and Hsiao (1982) suggest using the instrumental variable (IV) method to estimate the first differenced model. This technique eliminates the fixed-effect terms by differencing instead of within transformation. Since the lagged dependent variable is correlated with the error term, this method uses the second lagged difference as an IV. Although this method provides consistent estimates, Arellano and Bond (1991) developed a more efficient estimator, called differenced GMM, in order to estimate a dynamic panel difference model using all suitably lagged endogenous and other exogenous variables as instruments in the GMM technique (Roodman, 2009a). Blundell and Bond (1998) further developed a strategy named system GMM to overcome dynamic panel bias. Instead of transforming the regressors to purge the fixed effects and using the levels as instruments, the system GMM technique transforms the instruments themselves in order to make them exogenous to the fixed effects (Roodman, 2009a). The estimator in the differenced GMM model can have poor finite sample properties in terms of bias and precision when applied to persistent series or random-walk types of variables (Roodman, 2009b). The system GMM estimator allows substantial efficiency gains over the differenced GMM estimator provided that initial conditions are not correlated with fixed effects (Blundell & Bond, 1998). Thus, we use the system GMM method to estimate our dynamic supply models.

Several statistical tests are done to check the consistency of our preferred GMM estimator. First, the Arellano-Bond test for autocorrelation is used in order to test for serial correlation in levels. The test results, reported in the next section, indicate that the null hypothesis of no second-order autocorrelation in residuals cannot be rejected for nearly all production, acreage, and yield models, indicating the consistency of the system GMM estimators. Second, the Hansen test results cannot reject the null hypothesis of instrument exogeneity. We also conduct a test for the validity of the Blundell-Bond assumption using the difference-in-Hansen test of the two-step system GMM. The test statistics give *p*-values greater than 10% in all cases, suggesting that past changes are good instruments of current levels and that the system GMM estimators are more efficient. Furthermore, the standard error estimates for all specifications are robust in the presence of any pattern of heteroskedasticity and autocorrelation within panels. The Windmeijer (2005) two-step error bias correction is incorporated. Following Roodman (2009a, 2009b), we also "collapsed" the instrument set in order to limit instrument proliferation.

3.7. Results

3.7.1. Econometric results

Table 3.4 and Table 3.5 present the GMM results of the production/acreage and yield response functions respectively. For each respective crop, we estimate the supply models using pre-planting month spot prices and harvest period futures prices (except for rice) as proxy for expected prices at planting time.[22] We failed to find a significant supply-price relationship using futures prices (except for soybeans), which could imply that many agricultural producers do not make use of information on futures prices in forming their price expectations. Indeed, futures prices are good proxies for expected prices for producers in countries where domestic prices are strongly linked to the futures prices—that is, where the maturity basis is constant. Although the farmers in advanced economies participate widely in futures markets and the futures prices are linked to the cash prices, this is not the case in many developing countries. Thus, we reported the results obtained from the specifications with spot prices.

[22] Rice futures markets have relatively short time-series data, and local prices are unlikely to be strongly correlated with futures prices in several countries.

Table 3.4. Estimates of production and acreage response

	Production				Acreage			
Variable	*Wheat*	*Corn*	*Soybeans*	*Rice*	*Wheat*	*Corn*	*Soybeans*	*Rice*
Lagged dependent variable	0.96***	0..96***	0.93***	0.99***	0.99***	0.97***	0.93***	0.99***
	(0.01)	(0.04)	(0.04)	(0.02)	(0.01)	(0.03)	(0.03)	(0.00)
Wheat price	0.09**	-0.03	-0.21***		0.08***	0.01	-0.03***	
	(0.04)	(0.06)	(0.06)		(0.03)	(0.01)	(0.01)	
Corn price	0.08	0.24**	-0.04		-0.002	0.07***	-0.12***	
	(0.06)	(0.11)	(0.06)		(0.03)	(0.02)	(0.02)	
Soybean price	-0.02	0.06	0.36**		-0.05	-0.04*	0.15**	
	(0.05)	(0.06)	(0.16)		(0.03)	(0.02)	(0.07)	
Rice price	-0.01	-0.14**	-0.07	0.05***				0.03**
	(0.03)	(0.07)	(0.06)	(0.01)				(0.01)
Wheat price volatility	-0.69**	0.16	0.44**		-0.37**	0.12	-0.07	
	(0.29)	(0.28)	(0.17)		(0.14)	(0.15)	(0.16)	
Corn price volatility	0.49	0.30	-0.44**		0.25*	0.14	0.11	
	(0.45)	(0.23)	(0.17)		(0.13)	(0.09)	(0.15)	
Soy price volatility	0.36	-0.66	0.18		0.28**	-0.11	0.22**	
	(0.24)	(0.57)	(0.41)		(0.11)	(0.13)	(0.09)	
Rice price volatility				-0.25**				-0.11**
				(0.11)				(0.05)
Fertilizer price	-0.08**	-0.01	0.05**	-0.01	-0.01	-0.02	0.02	-0.01*
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1 ,174	1,444	1,371	1,342	1,162	1,418	1,350	1,342
F-test of joint significance: *p*-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Test for AR(2): *p*-value	0.15	0.15	0.07	0.09	0.89	0.29	0.98	0.14
Diff-Sargan test: *p*-value	0.99	0.99	0.98	0.99	1.00	0.99	0.99	0.98

Notes: All regressions are two-step system GMM. Two-step standard errors clustered by country, incorporating the Windmeijer (2005) correction, are in parentheses. Yield deviations are included in the acreage response models as additional control variables. *, **, and *** represent the 10%, 5%, and 1% levels of significance. All the production and area response models are weighted by the global crop acreage share of the respective country. Sensitivity analyses where we estimated elasticities using panels excluding countries in the rest of the world (ROW) group provide consistent results. Rice price and volatility are excluded in the non-rice acreage response models since land for rice cultivation is not usually suitable for these crops; however, competition in production is possible through input substitution.

In general, production, acreage, and yield responses to own prices are positive and statistically significant, consistent with economic theory. The results suggest that higher output prices induce producers to increase acreage and to invest in improving crop yields, implying that global food supply response to prices appears to occur through both acreage and yield changes. The production responses to own prices are larger than the respective acreage and yield responses (with the exception of the wheat yield response). The acreage and yield own-price elasticities are mostly similar in their order of magnitude.

The results show that soybeans and corn have the largest production responses to own-crop prices followed by wheat and rice. Conditional on other covariates, a 10% rise in the expected own crop price induces a production increase of about 4% for soybeans, 2% for corn, 1% for wheat, and 0.5% for rice in the short run. These production responses typically reflect the acreage and yield adjustments. An equivalent increase in the respective international crop prices induces farmers to increase their land allocated to soybean and corn cultivation by about 1.5% and 0.8%. Moreover, the yields of both soybeans and corn respond by an increase of about 1% following similar increases in international own crop prices. Global wheat acreage and yield also respond to output prices, with short-run elasticities of 0.08 and 0.17, respectively. In line with the production response results, rice has relatively weaker acreage and yield responses to own prices. Rice cultivation in some areas requires capital investment (such as canals and sluices) to ensure flooding at the time of planting. These investments are long-term decisions, implying that short-run price responses are inevitably low.

Additionally, the statistically significant cross-price elasticities have negative signs consistent with economic theory. Higher wheat prices are negatively correlated with soybean production, and corn producers respond to higher international rice prices by lowering corn production. The cross-price elasticities show that corn and soybeans compete for land at a global level, with a stronger corn price effect on soybean acreage than vice versa. In addition, higher international wheat prices lead to less land for soybean production.

Unlike own crop price levels, own-price volatility does not have a uniform effect on the supply of all crops. Price volatility seems to affect wheat and rice production most. The results reveal that an increase in the volatility of international wheat and rice prices leads producers to allocate less land to these crops and to reduce yield-improving investments, resulting in a decline in wheat and rice production. To some extent the negative wheat acreage response to own-price volatility could be offset if prices of competing crops such as corn and soybeans also exhibit such volatility. For corn, the negative supply impact of own-price volatility is due mainly to declining yields. While producers react to rising corn prices by using more inputs to improve corn productivity, corn price risk induces producers to shift inputs away from corn production. For soybean acreage, on the other hand, the estimated coefficients of wheat and own-price volatilities have a statistically positive sign. This result is consistent with previous national-level studies that find either insignificant or positive effects of price volatility on soybean acreage (e.g. de Menezes & Piketty, 2012). The majority of soybean producers in the world are large, commercial holders who are likely to be well informed about price developments. Thus, they are likely to be willing and able to absorb price risks.

Table 3.5. Estimates of yield response

Variable	***Wheat***	***Corn***	***Soybeans***	***Rice***
Lagged dependent variable	0.92***	0.96***	0.93***	0.98***
	(0.03)	(0.02)	(0.04)	(0.01)
Own-crop price	0.17***	0.09**	0.15***	0.06***
	(0.05)	(0.04)	(0.04)	(0.01)
Own-price volatility	-0.34**	-0.37**	-0.47**	-0.17**
	(0.16)	(0.17)	(0.23)	(0.06)
Fertilizer price	-0.07**	-0.01	-0.05**	-0.03*
	(0.03)	(0.02)	(0.02)	(0.01)
Time dummies	Yes	Yes	Yes	Yes
N	1,174	1,444	1,371	1,363
F-test of joint significance: *p*-value	0.00	0.00	0.00	0.00
Test for AR(2): *p*-value	0.05	0.43	0.08	0.13
Diff-Sargan test: *p*-value	0.96	0.74	0.93	0.84

Notes: All regressions are two-step system GMM. Two-step standard errors clustered by country, incorporating the Windmeijer (2005) correction, are in parentheses. *, **, and *** represent the 10%, 5%, and 1% levels of significance.

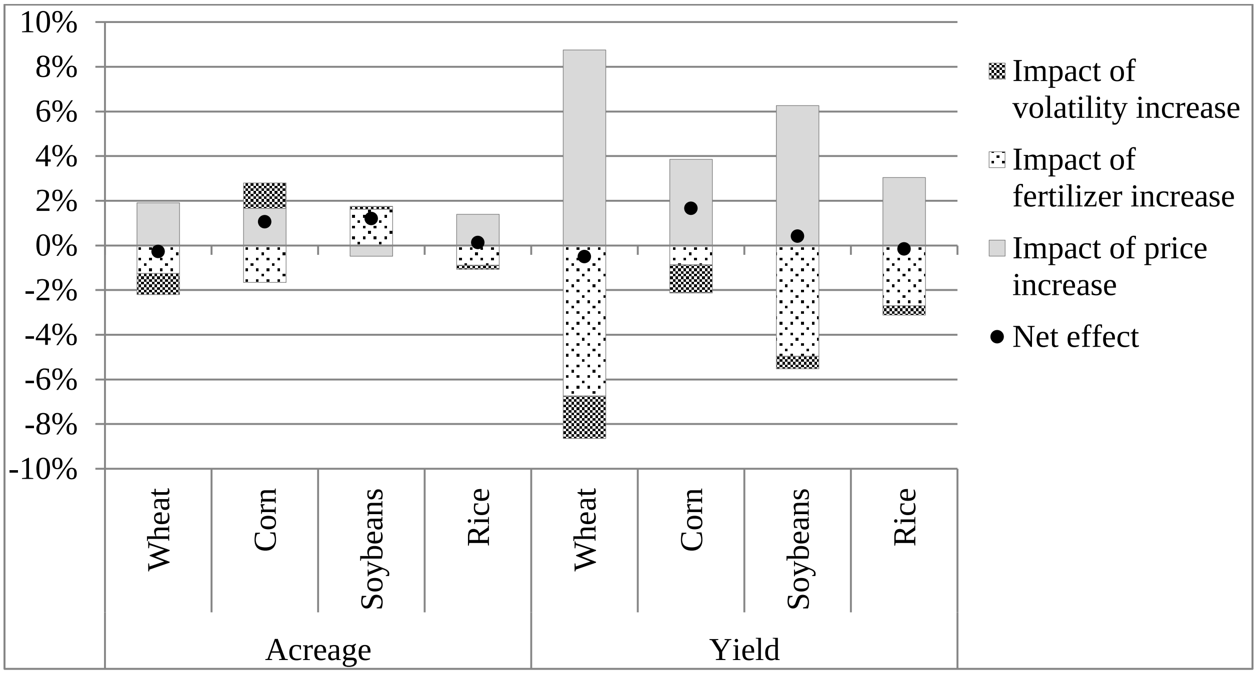
In addition to output prices, input prices are also important factors in farmers' production decisions, as shown by fertilizer price elasticities. Higher international fertilizer prices not only have a negative effect on wheat production and rice acreage, but also hold down the yields of nearly all crops. A doubling of international fertilizer price indices results in a 1% to 7% reduction in crop productivity.

The lagged dependent variables were both statistically and economically relevant in all crop supply models. The estimated coefficients indicate producers' inertia, which may reflect adjustment costs of crop rotation, crop-specific land (and other quasi-fixed and fixed inputs), technology, and soil-quality requirements. The coefficients of the lagged dependent variables may also, however, reflect unobservable dynamic factors, and interpretation should be made with caution (Hausman, 2012). The estimated coefficients of the lagged dependent variables are close to one, indicating that agricultural supply is much more responsive to international output prices in the longer term than in the short term.

In summary, our empirical results align with previous work and with the global time series results in the previous chapter showing that agricultural supply is inelastic in the short run (refer to Table 2.6). Apart from the soybean supply elasticities, which are of the same order of magnitude, our estimated elasticities are smaller than the weighted average of the national-level estimates. Despite the positive response of national crop supply to international prices, this discrepancy may hint that supply responses to domestic prices are relatively stronger.

3.7.2. Simulation results

The estimation of the price and volatility coefficients in Table 3.4 and Table 3.5 enables us to simulate the impacts of recent agricultural commodity price dynamics on acreage, yield, and production. To this end, we calculate the differences in the predicted outcome variables under the realized prices and under a counterfactual scenario where all output prices and volatility as well as fertilizer prices after 2006 are set equal to their 1980–2005 mean values. We consider only the direct short-term impacts and neglect the influence of the auto-regressive term, which would further exacerbate the changes in the long run. The results of these simulations are shown in Figure 3.1. and Figure 3.2. The net impact of increasing own and competing crop prices is a 1–2% increase in the area under cultivation of wheat, corn, and rice. However, the effect of higher prices of competing crop prices on soybean acreage outweighs that of higher own prices. In contrast, increasing fertilizer price reduces acreage by comparable amounts, except for soybeans, where it has a positive effect.[23] The coefficient for volatility is statistically insignificant for corn, but higher volatility affects wheat acreage negatively and corn acreage positively.



Note: The figure shows the impact of output and fertilizer prices, and output price volatility on acreage and yield compared with a counterfactual where these values were set to their long-term average. The net effect is calculated as the sum of the three components. The depicted rates refer to the net impacts during the five-year period 2006–2010. These changes are the direct short-term response, and they are the lower bounds for the longer-term effects as the coefficients of the autoregressive term are positive and closer to unity.

Figure 3.1. Impacts of the 2006–2010 price dynamics on acreage and yield

The overall impact of the 2006–2010 output and input price dynamics on acreage is estimated to be, on average, positive for corn and soybeans, negligible for rice, and slightly negative for wheat. The different price dynamics have greater impacts on yields, but because of strong opposing effects, the net impact is similar in magnitude to the impact on acreage allocation decisions. Own-price volatility tends to dampen yields by about 1–2% for the crops under consideration.

We use two approaches to calculate the impact of price level and price volatility on production. First, we simulate the impact on production using the estimated coefficients analogously to the

[23] One explanation for this is that soybeans require less nitrogen fertilizer than the other crops, which makes it more attractive when fertilizer prices are high.

acreage and yield calculation (direct method). We also calculate the production impact from the acreage and yield simulations by using the identity that production equals the product of acreage and yield (indirect method). The basic difference between these approaches is that the first one estimates the overall production effect directly from the observed data whereas the second one relies on the two-stage decision process where acreage and yield decisions are temporally decoupled. The results from both procedures are shown in Figure 3.2. Although the quantitative effects differ slightly, the findings are by and large consistent. The largest deviation between the two approaches is visible for soybeans, where the direct approach gives opposite directions for volatility, own-price, and fertilizer price impacts compared with the indirect approach. This deviation occurs because these variables have opposite effects on acreage and yield. The indirect estimation is driven by the yield simulation results because the acreage impacts are small. According to the direct method, the net impact of the 2006–2010 price dynamics on production is about a 6.5% increase for soybeans, a 3% increase for corn, negligible for rice, and about a 3% decrease for wheat.

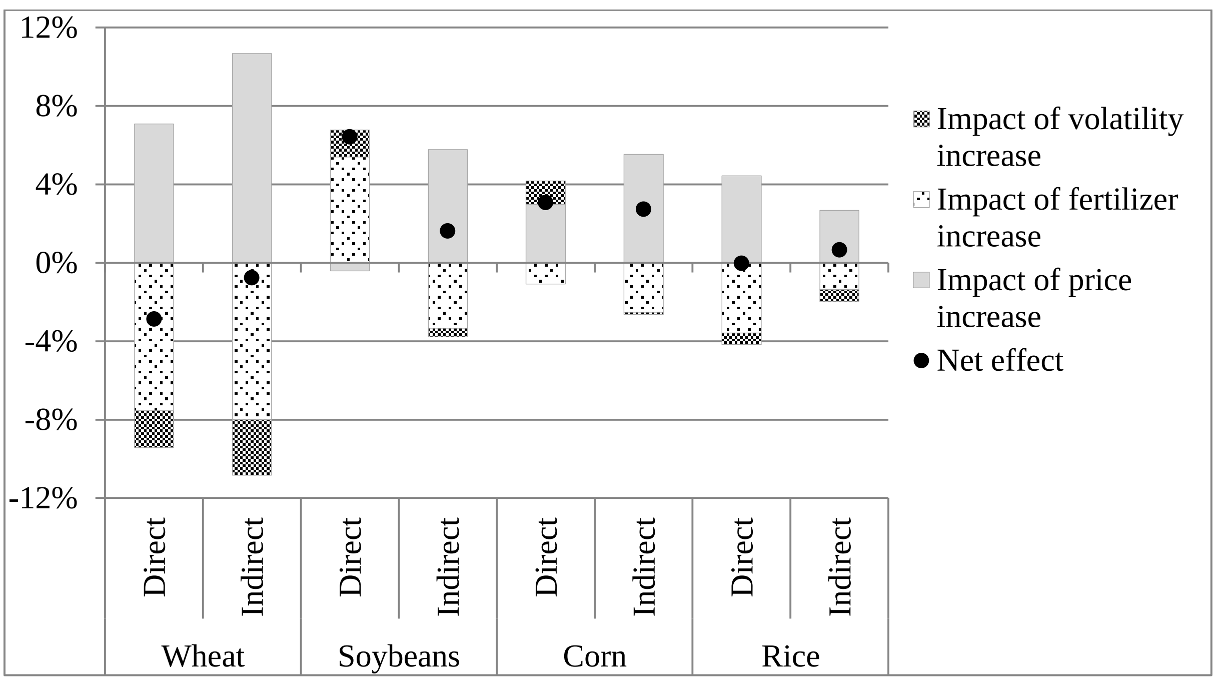


Figure 3.2. Impacts of the 2006–2010 price dynamics on production

In summary, the simulation results show that more volatile output prices and higher input prices have weakened the extent to which rising international agricultural commodity prices have increased output production since the middle of the last decade.

3.8. Conclusions

Uncertainty is a quintessential feature of agricultural commodity prices. Besides the traditional causes of price fluctuations, agricultural commodities are increasingly connected to energy and financial markets, with potentially destabilizing impacts on prices (Tadesse et al., 2014). Using cross-country panel data for the period 1961–2010, this chapter investigates the global supply impacts of international price levels and volatility. Estimation of the recent supply response to input and output price levels and output price volatility is a necessary step in predicting the future global food supply effects of developments in output price levels and volatility. In addition to responding to price changes by reallocating acreage, producers react to expected price changes by making decisions that affect yields.

The results underscore the relevance of output price volatility for the supply of the key global agricultural staple crops. Although higher risk in prices is usually associated with higher returns, economic theory shows that output price risk is detrimental to producers (Sandmo, 1971). Coefficients for the price-risk variables are statistically and economically significant in the supply response models for wheat and rice and in the yield response models for all crops. Besides inducing producers to shift land away from wheat and rice cultivation, higher output price volatility weakens their incentive to invest in yield improvement. For corn, own-crop price volatility has little or no impact on acreage allocation, but it has a negative impact on yield. Consequently, reducing agricultural price volatility is likely to increase food supply in the world and, more importantly, in developing countries. Some agricultural producers, however, do not shy away from making investments in order to obtain the higher returns associated with higher price risks. Such producers need not be hurt by output price volatility. The findings of the present study suggest that this is the case for the majority of soybean producers in the world. This result is relevant for policy makers because it suggests that a one-size-fits-all approach to price volatility management—such as through stockholding or public price risk insurance systems—would not be appropriate.

This chapter explains why the current high food prices have not brought about a large increase in global agricultural supply as one might expect. The estimated short-run supply elasticities are generally small. Agricultural supply does not, in the short run, increase on a par with output price increases. In other words, agricultural producers need more time to make necessary production adjustments and investments to increase supply. Furthermore, this study identifies for the first time how much the increased latent output price uncertainty represented by price volatility weakens the global positive supply response.

4. Short-term acreage forecasting model for staple food commodities

Abstract

The global supply of major grains like wheat, corn, and soybeans depends, particularly in the short term, on the acreage devoted to each of these crops and the yield obtained. Forecasting production is important to identify possible shortages in food supply and, thus, food security risks. Forecasting production, however, is also important for improved input allocation planning which affects agribusiness and the input supply industry. This paper explains methods and data used to forecast acreage response for major global producer countries. We focus on forecasting acreage – one of the two major determinants of grain production – three months before planting starts. According to basic economic theory, crop and input prices are used as major explanatory factors for acreage decisions: prices convey much information on agricultural fundamentals that are difficult to observe and quantify directly. One particular characteristic of the underlying study is that for *each country and each crop* the respective determinants are identified and used for forecasting. This allows us to account for the large heterogeneity in the countries' agricultural, political and economic systems in a country-specific model specification. The performance of the forecasting tool is assessed with ex-post prediction of acreage against historical data. Our forecasting tool includes major producer countries including USA, Brazil, Argentina, and the Russian Federation. All data, except the futures prices that are accessed from the Bloomberg database, are publicly available in the countries' respective agricultural statistical agencies.

Key words: Acreage forecasting, short-term acreage response, international prices, crops, price expectations

4.1. Introduction

The purpose of this chapter is to develop a short-term acreage response model for key crops, namely corn, soybeans, and wheat for selected major producing countries. In general, agricultural producers respond to own and competing output prices, input prices, price volatility, and other variables (Chavas & Holt, 1990; Coyle, 1993). Some variables such as rainfall and unexpected policy changes may not be available in advance. Thus, our estimations include the most important variables that are observable about three months before the planting season starts.

Producers respond to prices and other factors in terms of their land allocation for different crops at planting time (Just & Pope, 2001). Since harvest prices are not realized at the time of planting, producers need to form their price expectations about harvest-period prices. Depending on the respective countries and crops, we considered planting time cash prices and futures prices in order to proxy producer's expectations in the acreage response models. These prices contain more recent price information for producers and they are also closer to the previous harvest period, conveying possibly new information about the future supply situation. Besides own and competing crop prices, we considered the previous year's area, time trend as well as fertilizer and oil prices. Since global agricultural markets exhibit high frequency volatility, an annual model would do little to capture such intra-annual price dynamics and shocks. Thus, we developed an econometric model that enables us to forecast the planted area of each crop using intra-annual data. We have developed country and crop specific acreage response model specifications. This allows us to account for the large heterogeneity in the countries' agricultural, political and economic systems in a country-specific model specification.

Forecasting acreage before planting ensues is crucial for several reasons. First, it serves as an indication of how much food will be produced in the subsequent harvest season in the respective countries and for the respective crops. The selected countries and crops in our acreage forecasting model are major exporters and key staple crops in many countries, respectively. In other words, forecasting the amount of area allocated to these crops hints at the availability of food (a shortfall or an excess) at the international market, which has implications for global food security. For a given yield per hectare of land, forecasting acreage is an important first step in understanding and forecasting the entire production of the major crops. Second, it provides key information for input and crop protection supply industries to adapt their productions accordingly.

Our short-term models were validated by using historical data. As will be discussed later, in most cases our estimations have the right directional changes, and the confidence intervals provide a good assessment of the likely range.

4.2. Methodology

4.2.1. Acreage response model

A basic econometric supply model explaining acreage of a certain crop is formulated as a function of its own and competing crops' harvest-time prices, input prices and other exogenous factors. The producers make their optimal crop acreage choices subject to output prices that are not known at the time when planting decisions are made. Thus, expected rather than realized output prices are used for decision making. Information and expectations change rapidly in the course of a year and models that proxy expectations on previous annual average prices cannot capture short-term effects. As a consequence, we consider intra-annual price information in order to proxy producers' price expectations in our empirical acreage response models. Second, when applicable, the prior-to-planting season futures prices that mature at harvesting time are used to represent farmers' price expectations. In efficient markets, futures prices are an unbiased estimator of spot prices when the future contract matures (Gardner, 1976; Liang et al., 2011). When no futures prices are available (for example, in countries where commodity exchanges are missing), spot prices also convey relevant information about expected future prices due to intertemporal arbitrage of grain storage: If stocks are non-zero, current spot prices are in equilibrium with future prices and a change of expected future prices leads therefore to a change of spot prices (Fama & French, 1987; Hernandez & Torero, 2010).

Following the preceding two chapters, the implicit acreage response model can be specified as follows:

$$A_{t,i} = f\left[A_{t-1,i}, E\left(p_{t,i}\right), E\left(p_{t,j\neq i}\right), vol\left(p_{t,i}\right), Z_t, t\right] \qquad (4.1.)$$

where, $A_{t,i}$ and $A_{t-1,i}$ are planted acreages of crop i at period t and *t-1*, respectively; $E(p_{t,i})$ and $E(p_{t,j\neq i})$ are expected harvest time price of own crop i and competing crop j, respectively;

$vol(p_{t,i})$ is own crop price volatility; Z_t refers to variable input prices, namely fertilizer or crude oil prices; and t is a linear time trend in order to capture the effects of smooth over time trends including technological and demand changes.

Price expectations contain information that is relevant for farmers in their production decisions. Information regarding inventories, weather conditions, trade and other policies are implicitly accounted for in producers' price expectations. We, therefore, consider output prices to be the most important variable to shape farmers acreage allocations. Figure 4.1 shows how the intra-annual acreage allocation decisions of a typical US farmer might be affected by several factors. Having information about winter wheat harvest in the US itself and (partial) spring harvest of corn and soybeans in major producers in the South (e.g. Brazil, Argentina), a US farmer adjusts his price expectations for planting soybeans and corn in the spring season – which will be reflected in the US futures prices and spot prices. Therefore, crop prices two to three months before planting as well as futures prices contain such important information for the farmer.

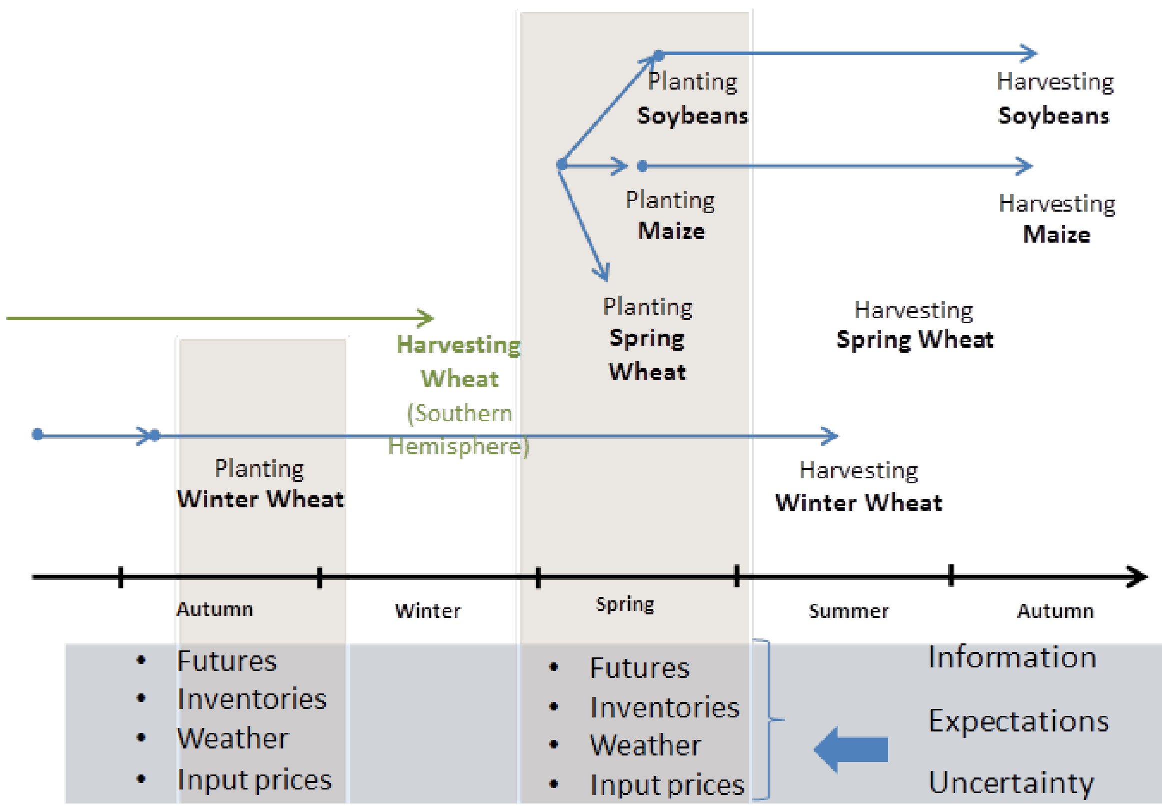


Figure 4.1. Intra-annual acreage allocation of a typical US farmer

4.2.2. Data and country profiles

The acreage forecasting model in this chapter relies on data from different sources covering the period 1991-2013. The empirical model utilizes country-level data to estimate global acreage responses for the key world crops. The national level sources of planted acreage for those countries where we have obtained planted acreage are presented in the Appendix (Table A9). However, for countries where could not obtain planted acreage, we instead use harvested acreage obtained from Food and Agriculture organization (FAO) of the United Nations, the United States Department of Agriculture (USDA), or from governmental sources as a proxy. Table 4.1 shows the correlation between harvested and planted area for those countries where we have obtained acreage planted data from national statistical offices. The correlation coefficients are mostly (except in the case of wheat for the USA) close to unity, indicating that data on harvested acreage can be used as good proxy for planted acreage in our econometric models. The international spot market output prices, crude oil prices and fertilizer price indices were obtained from the World Bank's commodity price database.

Table 4.1. Correlation coefficients of planted and harvested area data

	Correlation coefficient		
Country/crop	Wheat	Soybean	Corn
Argentina	0.99	0.96	0.98
Australia	0.88		
Brazil		0.96	0.99
Canada	0.89		
United States	0.76	0.99	0.99

Note: correlation coefficients were calculated using harvested area data obtained from FAO-AMIS and planted area from national statistical sources for the period 2000–2013.

We include the major producing countries of the selected crops in our acreage forecasting models. For instance, about 70% of the global area under soybean cultivation is found in just three countries, namely, USA, Brazil, and Argentina. While the United States has been the dominant producer of soybeans for a long time, large soybean expansions are observed in Brazil and Argentina over the recent decades. According to data from the Foreign Agricultural Service (FAS) of the USDA, the two countries alone account for half of the total soybean production in the 2013/2014 marketing year. The other countries for which we have attempted to make soybean acreage forecast is Ukraine since it is a country with one of the fastest soybean acreage expansions in the last few years. Wheat and corn, on the other hand, are produced in relatively more diversified countries and geographical zones. Nevertheless, about a third of the global planted acreage of corn is found in the USA and Brazil; and about a fourth of the global planted acreage of wheat is found in the USA and the Russian Federation. There are two seasons for corn in Brazil: while the first is harvested early in the calendar year, the second is harvested in the beginning of the northern hemisphere summer. There seems to be a tendency of moving to the second corn in Brazil in recent years. In summary, the countries for which we conducted acreage forecasting constitute about 70%, 40% and 35% of the global area under soybean, wheat and corn cultivation, respectively (Figure 4.2).

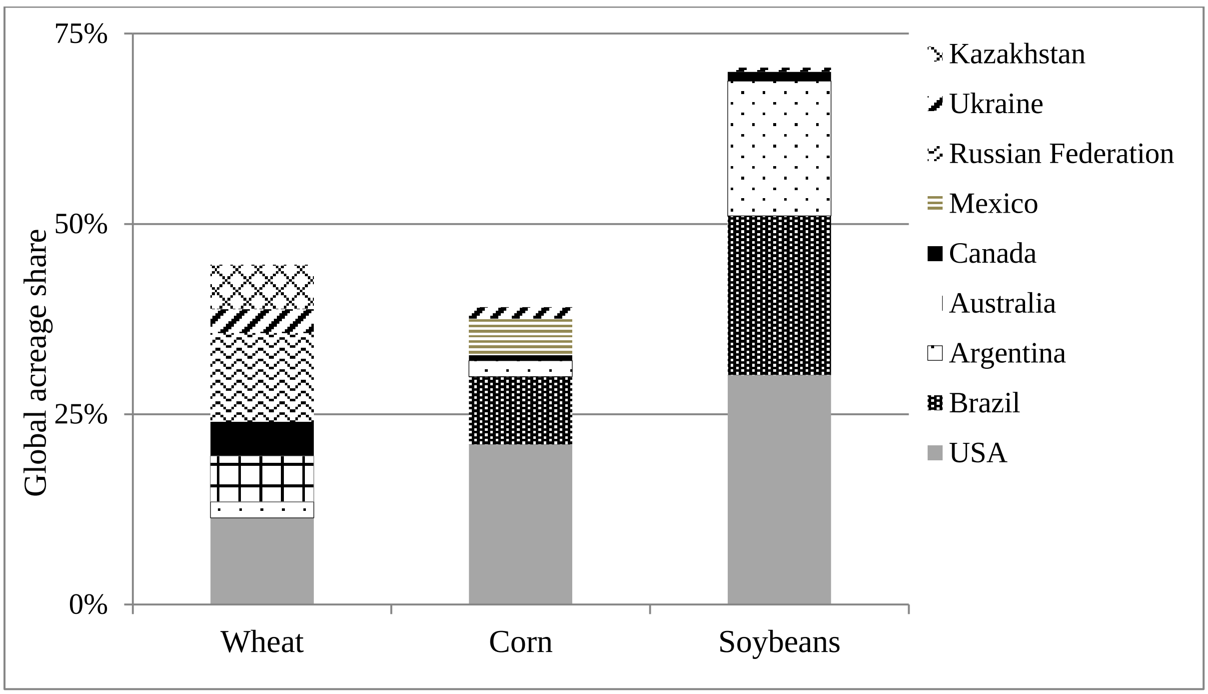


Figure 4.2. Acreage share of countries included in our forecasting tool

4.2.3. Estimation technique

For the empirical estimation, we apply a reduced form Autoregressive Distributed Lag (ARDL) acreage response model:

$$A_{t,i} = \beta_{0,i} + \beta_1 A_{t-1,i} + \sum_j^n \alpha_{ij} E_t(p_{ij}) + \beta_2 Z_{t-1,i} + \gamma t + \varepsilon_{t,i} \qquad (4.2)$$

where the variables are as defined above.

Our general procedure is to have different model specifications for each country and each crop based on the crop calendar[24] and other characteristics of the country (i.e. regarding planting and harvesting time, existing of futures exchange, relevance of competing crops etc.). This gives us a set of *a priori* specifications based on theoretical considerations. We then run regression models on these specifications with different crop prices (e.g. domestic wholesale spot prices, futures prices, international spot prices) and input prices (fertilizer and oil prices). After testing several model specifications, we ultimately chose the model with the highest predictive power adjusted for the number of considered variables (adjusted R-squared) and with the smallest root mean squared error (RMSE). The final model is the one which explains acreage the best with the minimum necessary data input.

Some land is more appropriate for a certain crop than for another, and producers might have to incur adjustment costs to rotate land for crops. Therefore we expect a positive coefficient on last year's own crop acreage. While higher own crop prices imply larger expected profits (positive coefficient), higher prices of competing crops induce producers to shift land away from the respective crop (negative coefficient). Fertilizer and oil prices indicate production costs and the higher such costs, the lower the incentive to cultivate more land. Thus we expect a negative coefficient for these variables. However, higher oil price also indicates more demand for biofuel and we may have a positive coefficient, especially for corn. High fertilizer prices may also have a positive effect on the acreage of some crops. This is typically the case for soybeans. Soybean production requires little or no nitrogenous fertilizer and higher fertilizer prices therefore may imply that it is less costly to cultivate more land for soybean production, shifting away from crops with large fertilizer demand. Large output price variability introduces a risk for producers and this may induce farmers to shift land to crops with less volatile prices[25]. Last but not least, the time trend measures the effect of smooth changes such as population, income and technology on crop acreage over time. With the coefficients of these variables for each country and each crop, it would then be possible to forecast acreage.

For all of the variables in the autoregressive distributed lag models for the area forecasts, the values have been transformed into their logarithmic formats in the econometric models. Hence,

[24] Refer to Tables A5-A8 in appendix I for the crop calendar information of these countries.
[25] Since we have few observations, we exclude the price volatility measure in our country-specific empirical model specifications.

the estimated coefficients can be interpreted as acreage elasticities. Therefore, to calculate the total area, one cannot just take the exponential of the estimated logged variable. Instead, if the equation is of the ARDL form given above, one has to calculate

$$\hat{A} = \hat{\alpha}_0 \exp\left(\widehat{\log A}\right) \quad (4.3)$$

where the “hat” specifies the estimated variables and

$$\hat{\alpha}_0 = \frac{1}{n}\sum_{i=1}^{n} \exp \hat{\varepsilon}_i \quad (4.4)$$

where n is the total number of observations (Wooldridge, 2009)

We conducted the Augmented Dickey-Fuller (ADF) unit root test in order to check the stationarity of the variable series in our acreage models for each crop and country. The results from the ADF test are reported in Table 4.2 for each crop. The test results have four different outcomes, with different implications for the consequent estimation technique.

First, all the variable series in some acreage model specifications are mean-stationary. This is, for instance, the case for the variables in the Argentine soybean acreage model. Accordingly, we run an OLS regression on level variables. Second, the dependent variable is stationary whereas all the independent variables (except the lagged dependent variable) are no-stationary series. This is the case for all crop acreage response models in Ukraine; wheat in the US and the Russian Federation; and Corn in Mexico. In such circumstances, including lagged values of the dependent and independent variables as regressors helps to avoid the problem of spurious regression. Since we have both the lagged dependent and independent variables as explanatory variables in our specifications, our estimated coefficients are asymptotically consistent.

Third, neither the dependent nor the independent variables are mean stationary (they are integrated of order one); however, they are cointegrated in the long-run. In other words, they have a stationary linear relationship. Table 4.3 provides the cointegration test results based on the Engle and Granger’s two-step procedure (Engle & Granger, 1987) for country and crop combinations with all I(1) variable series from the first step ADF results (see Table 4.2). In our case, the variables in the empirical models of corn in Argentina, Brazil (2^{nd} corn), and the US; wheat in Canada and Kazakhstan; and soybeans in Brazil and the US have such results. In such circumstances, OLS estimation is super consistent and the estimated coefficients converge to the true parameters much faster than otherwise.

Table 4.2. Unit root (ADF) test statistics (Ho: unit root)

				Corn			
Variable		Corn acreage	Wheat price	Corn price	Soy price	Fertilizer price	*Oil price*
Argentina		-1.99	–	-2.29	-2.27	-0.91	0.09
Brazil	1st Corn	–	–	-1.61	-1.78	-1.59	–
	2nd Corn	-2.29	–	-1.27	–	-1.15	–
Mexico		-3.75	–	-1.25	–	-0.91	-0.22
Ukraine		-3.48	–	-0.10	–	0.98	0.24
USA		-2.64	–	-1.39	-1.61	-1.76	-0.86
				Wheat			
Variable		Wheat acreage	Wheat price	Corn price	Soy price	Fertilizer price	*Oil price*
Argentina		-2.74	-1.62	–	-0.96	–	–
Australia		-2.82	-2.37	–	–	-1.01	-0.86
Canada		-2.47	-1.46	–	–	–	–
Kazakhstan		-2.72	-1.72	-1.41		-0.96	-0.24
Russian Federation		-3.45	-1.52	-1.32	–	–	-0.24
Ukraine		-4.06	-1.64	-1.13	-1.04	–	-0.98
USA		-4.29	-1.09	–	–	-1.76	-0.86
				Soybeans			
Variable		Soy acreage	Wheat price	Corn price	Soy price	Fertilizer price	*Oil price*
Argentina		−5.22	–	−2.71	−2.69	−0.91	–
Brazil		−2.78	–	−2.06	−1.93	−1.76	–
Ukraine		−3.41	-1.16	−0.10	−0.86	−0.98	–
USA		−2.54	–	−1.71	−1.82	−1.76	−0.86
Critical value (10%)		***−3.20***	***−2.62***	***−2.62***	***−2.62***	***−2.62***	***−2.62***

Notes: Critical values are taken from Fuller (1976, p. 373). The results are ADF tests with one lag and with time trend for the acreage variables whereas we add no lag but a drift for the price variables.

Last but not least, neither are any of the variable series in the acreage models stationary (Table 4.2) nor are they cointegrated (Table 4.3). The variables in our wheat acreage response models for Argentina and Australia, and those of 1st corn in Brazil as well as their linear relationships are all I(1) series. Thus, we included the first order difference of the I(1) variables in these models to avoid spurious regression results.

Table 4.3. Cointegration test results (Ho: no cointegration)

Country	Crop	T-statistic
Argentina	Corn	-5.08
	Wheat	-2.51
Brazil	1st corn	-1.43
	2nd corn	-3.32
	Soybeans	-3.24
Australia	Wheat	-1.41
Canada	Wheat	-4.46
USA	Corn	-3.77
	Soybeans	-3.49
Kazakhstan	Wheat	-3.20
Critical value		**3.20**

Note: The alternative hypothesis (H1) is that there is at least one cointegration relationship in the long run.

Moreover, because the lagged endogenous variable implies autocorrelation in our econometric estimations, we employed the Newey-West autocorrelation adjusted standard errors.

Limitations/Caution with regard to our acreage forecast

It is important to be aware of the limitations of our model approach, especially with regard to our forecasting results. The limitations of the model are typically due to limited data availability: either because we can use only few observations over time or because we use only aggregated national data.

As the model is based on *prices* as the most important (and easily measureable) determinants of supply response, it will have limited predictive power in cases where non-price factors are more important. This is the case if governments implement ad-hoc policies and controls; if farmers produce crops mainly for their own consumption; if farmers have limited market access; if farmers selling prices are systematically different from the reference prices we consider (e.g. in case of imperfect price transmission or non-convergence of futures and spot prices); or if other subsidies and taxes dilute the incentive role of prices.

As explained above, spot prices at planting time are often good proxies for expected futures prices as there is an intertemporal dynamic relationship between the two price series. This relationship, however, can change if interest rates, storage costs or storage policies change and if stocks are depleted. Finally, our model assumes a stable relationship between acreage and the explaining factors. In countries that experience large transformations of the agricultural sector, the elasticities on price are likely to change over time. For example, we would expect that in a former socialist country (with a centrally planned economy) which has changed to a decentralized market economy experience increasing supply elasticities as farmers respond more and more to prices during the transformation process. In our model, we assume average price elasticity for the entire time horizon. Nevertheless, we have typically considered periods after 1991 in order to reduce this problem. Changing elasticities requires updating of the regressions every couple of years to avoid biased forecasts, which is not feasible with few observations.

4.3. Results and discussion

In this section, the results of all three crops and all countries for which we have conducted acreage forecasting are presented.

4.3.1. Estimation results

Tables 4.4–4.6 present the ARDL model estimation results for corn, wheat and soybean acreages respectively. In general, the regression estimates illustrate that own and competing crop prices have positive and negative coefficients respectively, consistent with economic theory.

One can see from Table 4.4 that corn acreage responds to its own prices with elasticities that range from 0.1% in Mexico to as high as 0.6% for second Corn in Brazil. A 10% higher corn price, for instance, leads to an expansion in corn acreage by about 4% in Argentina, 2% (1^{st}) and 6% (2^{nd}) in Brazil, 1% in Mexico, and above 3% in the US. Not only is the price response of the 2^{nd} corn (also called Safrinha) in Brazil stronger, its acreage is also increasing at annual rate of 6%. As a consequence, area under cultivation of Safrinha corn in Brazil took the lead over the first corn (also called Safra) during the 2012 planting season. While corn acreage negatively responds to fertilizer price index, it has positive albeit mostly statistically insignificant response to international crude oil prices. As it is theoretically expected, high (input) fertilizer price reduces producers' profit expectations and they tend to shift land away to crops with little or no fertilizer demand. High crude oil price, on the other hand, has two opposite effects. On the one hand, higher oil price implies large production cost and hence its effect is expected to be negative. On the other hand, higher oil price imply larger demand for biofuel, and hence for corn, and hence its acreage effect is positive. The net effect seems to be statistically negligible in our empirical estimations except for Corn in Mexico where the latter effect outweighs.

Table 4.4. Estimation results for corn

Variable	Argentina	Brazil		Mexico	Ukraine	USA
		1st Corn	2nd Corn			
Last year area	0.76***	-0.59**	0.20	-0.47**	-0.24	-0.01
	(0.09)	(0.19)	(0.14)	(0.21)	(0.29)	(0.14)
Own crop price	0.41**	0.21*	0.57***	0.10*	0.34	0.34**
	(0.19)	(0.11)	(0.10)	(0.05)	(0.26)	(0.10)
Soybean price	-0.41**	-0.32**	–	–	–	-0.16*
	(0.19)	(0.14)				(0.11)
Last year fertilizer price	–	0.22**	-0.28***	-0.12***	-0.24	-0.03
	–	(0.08)	(0.07)	(0.04)	(0.28)	(0.03)
Last year oil price	0.06	–	–	0.11**	0.50	0.03
	(0.04)			(0.04)	(0.48)	(0.03)
Time trend	–	-0.004***	0.06***	-0.02***	0.05	0.003
	–	(0.002)	(0.01)	(0.005)	(0.04)	(0.002)
Constant	2.06**	6.96*	-119.36***	59.33***	-92.16	4.16
	(0.73)	(3.66)	(24.34)	(12.11)	(69.73)	(3.74)
N	24	23	23	21	21	28
Adjusted R-square	0.77	0.89	0.98	0.71	0.73	0.85

Notes: Figures in parentheses are Newey-West autocorrelation adjusted standard errors.
*P < 0.10, **P < 0.05, ***P < 0.01.

Although elasticities are smaller than for the corn acreage model, wheat acreage in the different countries exhibits a positive response to own prices (Table 4.5). Price elasticties of wheat acreage range from about negligible in Kazakhstan to about 0.3% in the Russian Federation. It is also interesting to see that wheat acreage in these countries has a decreasing trend over time. It is also noteworthy to mention the positive coefficient of the international oil price variable on the wheat acreage models of Kazakhstan and the Russian Federation, which is contrary to our expectations. One explanation could be that larger export revenues as a result of higher international oil prices have a substantial share in national income of these countries and these might (partly) be invested into agriculture.

Table 4.5. Estimation results for wheat

Variable	Argentina	Australia	Canada	Kazakhstan	Russia	Ukraine	USA
Last year area	-0.09**	-0.22	0.39*	0.40***	-0.35***	-0.20	0.49**
	(0.17)	(0.19)	(0.20)	(0.08)	(0.12)	(0.22)	(0.21)
Own crop price	0.14	0.14*	0.12***	0.03	0.26***	0.35	0.13**
	(0.26)	(0.08)	(0.04)	(0.10)	(0.07)	(0.24)	(0.06)
Soybean price	0.18	–	–	–	–	-0.31	–
	(0.35)					(0.48)	
Corn price	–	–	–	-0.04	-0.29***	-0.19	–
				(0.08)	(0.07)	(0.27)	
Last year fertilizer price	–	0.21**	–	-0.07	–	0.32	-0.08**
		(0.09)		(0.05)		(0.35)	(0.04)
Last year oil price	–	-0.24**	–	0.23***	0.24***	–	-0.01
		(0.11)		(0.06)	(0.06)		(0.03)
Time trend	-0.01	-0.001	-0.01**	-0.01**	-0.02***	-0.01	-0.005
	(0.01)	(0.003)	(0.005)	(0.004)	(0.004)	(0.02)	(0.003)
Constant	26.25	2.04	33.92**	26.02**	49.15***	24.42	15.49*
	(16.00)	(3.94)	(12.35)	(9.80)	(10.42)	(35.51)	(8.71)
N	20	24	24	21	21	21	28
Adjusted R-square	0.54	0.43	0.78	0.69	0.60	0.21	0.84

Notes: Figures in parentheses are Newey-West autocorrelation adjusted standard errors.
*P <0.10, ** P <0.05, *** P <0.01.

In terms of the results from the soybean acreage response model, Ukraine seems to have the largest response to both own and competing crop prices. Soybean acreage in Ukraine seems to have a unitary positive own price elasticity, indicating that a 10% higher own crop price induces a 10% soybean acreage expansion. Soybean acreage in all the four countries in Table 4.6 does exhibit a strong upward trend, with annual growth rates ranging from 1% in the US and as high as 10% in Ukraine. Besides the strong price response, the results show that demand and other technological changes might have contributed to the acreage expansion of soybeans in Ukraine. Such smooth over-time changes, for instance, increases in population, income, and technology, seem to bring about higher land demand for soybean production in all these countries.

Table 4.6. Estimation results for soybeans

Variable	Argentina	Brazil	Ukraine	USA
Last year area	0.76***	0.62**	0.81***	0.44*
	(0.13)	(0.22)	(0.08)	(0.20)
Own crop price	0.03	0.14	0.95*	0.13
	(0.10)	(0.17)	(49)	(0.10)
Corn price	-0.04	-0.02	-0.67***	-0.17*
	(0.10)	(0.17)	(0.21)	(0.09)
Wheat price	–	–	-0.99**	–
			(0.43)	
Last year fertilizer price	-0.08	-0.17**	-012	0.05*
	(0.05)	(0.08)	(0.26)	(0.02)
Last year oil price	–	–	–	-0.07**
				(0.03)
Time trend	0.02*	0.03**	0.10***	0.01**
	(0.01)	(0.01)	(0.02)	(0.005)
Constant	-39.64*	-48.12**	-191.82***	-16.77**
	(22.32)	(20.41)	(43.55)	(7.44)
N	24	23	21	28
Adjusted R-square	0.98	0.97	0.98	0.86

Notes: Figures in parentheses are Newey-West autocorrelation adjusted standard errors.
*P <0.10, ** P <0.05, *** P <0.01.

4.3.2. Forecasting results (out-of-sample forecast)

Figure 4.3 depicts the validation of the acreage forecasting model using historical data for corn, wheat and soybeans in the upper, middle and bottom panel of the graph, respectively. Depending on the respective crop's planting season and availability of data (3 months before planting), the figures also show out-of sample acreage forecasts.

In general the predicted acreage is correct in terms of direction. Moreover, the actual data points are mostly in the 90% confidence interval, showing good prediction power when validated with historical data. While the corn acreage response models in Argentina, the US and Brazil have good prediction power, those of Mexico and Ukraine have a wide error margins implying less reliable out-of-sample forecasts.

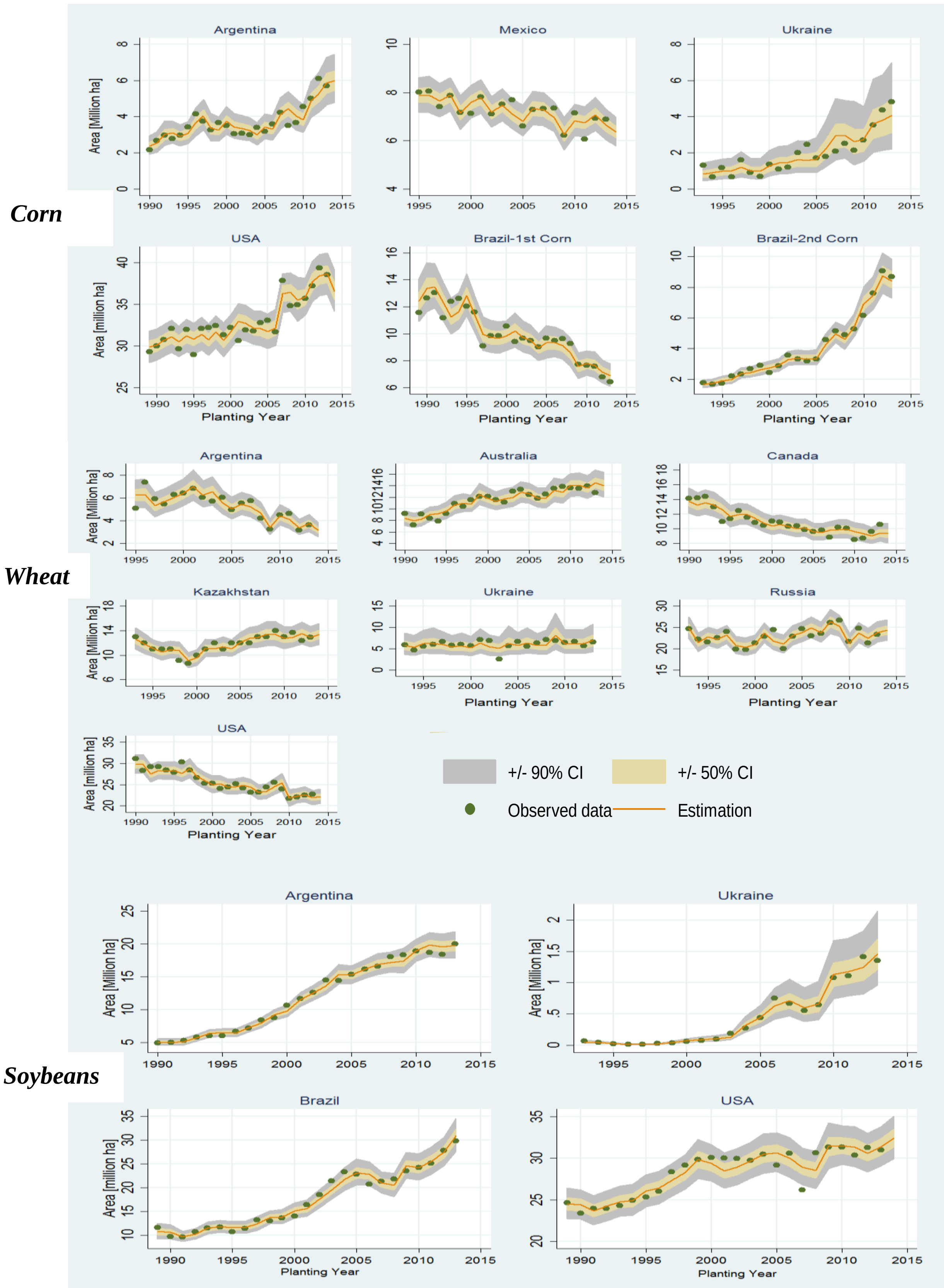


Figure 4.3. Forecasting and validation of acreage response model estimations

Similarly, one can observe relatively better acreage prediction in the case of soybeans. Besides the R-square value which is relatively high for soybean acreage, the graph also shows that the observed data points are very close to the predicted line, especially for Argentina and Brazil. Apart from the 2007 planting season, the soybean acreage response model is also able to fairly predict planted acreage in the US.

4.4. Conclusions

The main results of our empirical forecast models are depicted in Tables 4.4‒4.6. A substantial part of our analysis in this chapter has been to identify the relevant determinants of acreage supply for each crop and country and to select the model which provides the best prediction power (high explanatory power) with few input data requirement. These acreage elasticity results are also important robustness checks for the worldwide aggregate acreage elasticity estimates of Chapters two and three above. Based on the results, the world-wide aggregate results can be said to adequately show an average effect of prices on acreage for each crop. The country specific acreage elasticities can be used as inputs in acreage forecasting applications for the respective countries and crops. To this end, an Excel-based user interface, which uses the information from the country-specific acreage results, is established to calculate the forecasted area based on the relevant current information.

With the help of the results reported above, it is possible to identify two groups of markets (Table 4.7): those with *high price responsiveness* (where prices key drivers of acreage) and those with *strong time trends* (where acreage growth can be expected even when prices are changing slowly). Markets with high price responsiveness (i.e. own-price elasticity higher than 20%) include: Corn in Argentina, Brazil (both 1st and 2nd corn), the US, and Ukraine; wheat in the Russian Federation and Ukraine; and soybeans in Ukraine. Countries and crops where acreage is expected to grow/decline by more than 2% per year (without any changes in prices or costs) include: Corn in Brazil (2nd corn) and Ukraine; soybeans in Argentina, Brazil and Ukraine; and wheat in Russian Federation. In these cases, acreage expansion/shrinkage can be expected even if prices remain stable or are slightly decreasing.

Input costs (fertilizer prices) are in most cases insignificant – one reason might be that international fertilizer prices are not strongly linked to national prices due to government subsidies in some countries. Fertilizer prices reduce soybean and wheat acreage in Argentina, and soybean and 2nd corn acreage in Brazil. Higher oil prices also reduce wheat acreage in Australia and that of soybeans in the US. On the other hand, increasing oil prices boost extensification in Kazhakstan and Russian Federation – where revenues from oil exports have a substantial share in national income and might be (partly) invested into agriculture.

Table 4.7. Overview of the price sensitive markets and the markets with strong time trends

Crop	*Price sensitive markets*	*Markets with strong time trends*
Corn	Argentina (0.41) Brazil (1st: 0.21, 2nd: 0.57) USA (0.34) Ukraine (0.34)[a]	Brazil (2nd: 0.06) Mexico (-0.02) Ukraine (0.05)[a]
Wheat	Russia (0.26) Ukraine (0.35)[a]	Australia (0.03) Russia (0.02) Argentina (0.02)
Soybeans	Ukraine (0.95)	Brazil (0.03) Ukraine (0.10)

Note: The respective coefficients are given in parentheses.
[a] These coefficients are not statistically significant at the 5% level.

While we are able to explain historical acreage fluctuation well for most countries and crops, forecasting power is weak for some particular cases. Our model, for instance, has weak explanatory power for wheat acreage in Ukraine. Nevertheless, we are able to adequately explain historical acreage decisions and to give a timely forecast for the upcoming planting season based on the currently and publicly available data in the remaining cases. The calculated point forecast is extended by an interval estimation which helps to assess the likely range of the acreage allocation. This is important to appropriately deal with uncertainties and risks as forecasts are usually uncertain.

It should be kept in mind that the forecast is primarily based on price movements as a major determinant of acreage. The forecasting tool could therefore be extended by further market analyses based on broader political and economic factors as well as short-term weather events, which are not accounted in by prices but that could potentially influence acreage decisions.

5. Price expectation formation of smallholder farmers in Ethiopia: The role of information

Abstract

Economic agents use different information when making decisions on their economic activities. Given the intrinsic feature of agriculture that there is a time lag between production decision and output realization, price expectation plays a crucial role in the production, marketing and agricultural technology adoption of farmers. The empirical findings show that information regarding current and past output prices in nearby grain markets, central wholesale prices and seasonal rainfall shapes smallholders' price expectations. Moreover, the results suggest that farmers who invest more in acquiring better price information and who reside closer to grain markets are more likely to have smaller price forecasting error margins. On the contrary, farmers with high discount rates are more likely to have larger forecasting errors. Accordingly, it might be necessary for the government to provide market information as a public good through organized market information systems. Thus, improving both information and physical infrastructures is important. Agricultural extension agents could assist in the process by disseminating timely and accurate output and input price information from nearby grain markets to farmers in local villages.

Keywords: *Price expectations; prediction accuracy; information set; smallholders, agriculture; Ethiopia*
JEL code: *D81; D84; Q11; Q13*

5.1. Introduction

Economic agents use different information when making decisions on their economic activities. Among many, past trends, outcomes in related markets, media reports, weather and published forecasts are some of the information that agents use in their resource allocation decisions (Just & Rausser, 1981). The intrinsic feature of agriculture that there is a time lag between production decision and output realization makes the role that information plays for agricultural producers indispensable. Besides, agricultural production is inherently stochastic due to weather shocks, pest infestations and other shocks, which affect the general market supply condition and therefore prices. Thus, agricultural producers depend on their price expectations in order to make their production decisions. Farmers, therefore, involve themselves in gathering and processing price and other information, which they believe affects prices at harvesting time. Producers' price expectations play a crucial role in any agricultural supply response study (Moschini & Hennessy, 2001). Thus, understanding what information set producers use and modelling how this information set is utilized in their production decisions have been an integral part of agricultural supply response models (Fisher & Tanner, 1978; Holt & McKenzie, 2003).

The information set and the relevance of each of the constituting elements widely vary across producers depending on their access to information, education level, geographical context and their ability in processing information (Chavas, 2000). This chapter focuses on smallholders in rural Ethiopia where published price forecasts are non-existent and where literacy rate is quite low. Nevertheless, as any other agricultural producer, these rural households have their own information set to form price expectations on which they base their agriculture production decisions. Smallholder farmers are dynamic actors who respond to economic incentives and risks that they perceive in their environment (von Braun, 2004). Although availability of information depends on government actions as well as institutional and technological innovations, it was since long time ago that studies indicated the efficiency of smallholder farmers in their resource utilization (Schultz, 1964). By his seminar research in 1964, Schultz clarified that smallholders are efficient nevertheless poor. This study attempts to understand the information resource relevant to such farmers and how efficiently they utilize the available information in their price expectation formations.

Several approaches have been applied to model expectations of economic agents. Naïve, adaptive and rational expectations are the most commonly applied approaches in agricultural markets. The naïve expectation hypothesis (Ezekiel, 1938) assumes that future prices will be the same as current prices. Thus, a naïve farmer forms his expectation about futures prices based on the prices today. The adaptive expectation hypothesis (Nerlove, 1956), on the other hand, assumes that price expectations evolve overtime in the sense that farmers make adjustments in their expectations depending on past errors. The adaptive price expectation model is consistent with the moving-average process by which economic agents learn from their past behavior. The other expectation hypothesis, which has been dominant since the 1960s, is the rational expectation hypothesis (Muth, 1961). The rational expectation hypothesis, in its strong sense, assumes that expectations are consistent with the underlying market structure and that economic agents make efficient use of all available information for their price expectation formation. In other words, this hypothesis assumes that agents know the true data generating process (Evans & Ramey, 2006). Although it is not applicable for rural smallholders with no access to futures markets, which are the focus of this chapter, futures prices have also been used as proxy for price expectations (Gardner, 1976).

Since obtaining and processing information is costly, it may be less likely that producers make use of all available information to form their price expectations (Orazem & Miranowski, 1986). This is even so in the context of subsistent smallholder farmers with limited access to information and capital. Thus, the fully rational expectation hypothesis has less realistic practical application in our context. This hypothesis is also rejected in several experimental and survey datasets (Nelson & Bessler, 1992; Nerlove & Schuermann, 1995). Furthermore, the implementation of the rational expectation hypothesis is complicated for the applied econometrician. For these and other practical issues, recent research has focused on modelling supply response models using a quasi-rational price expectation, which is consistent with price prediction from a reduced-form dynamic regression equation (Holt & McKenzie, 2003). The quasi-rational expectation hypothesis has more realistic assumptions about economic agents' information set and their data processing knowledge. Empirical applications also show the relevance of this approach in their supply models (Holt & McKenzie, 2003; Nerlove & Fornari, 1998).

This chapter has two main objectives. First, it identifies the relevant variables that constitute the information set of a typical smallholder farmer in his/her price expectation formation. The importance of each of the elements in the information set is investigated. Second, we explain the efficiency of smallholder farmers in their price expectations. In other words, we address the question, 'who are the good predictors and does information play a role?' in the context of smallholder farmers in rural Ethiopia. There may be several factors that explain why some farmers predict harvest time output prices more accurately than others; however, we give more emphasis on the role of information, the role in particular of Information and Communication Technology (ICT). Given the limited number of previous studies of actual price expectations and the availability of several theoretical models of price expectation formulation, this study may provide some new insight into how smallholding farmers are actually forming their price expectations. Analysis of their actual expectations and the distribution of their expectations relative to realized prices may assist agricultural economists and policy makers to deliver price outlook and price risk management strategies information, and researchers estimating supply response models to choose more appropriate specification of price expectation.

The rest of this chapter is organized as follows: the following section presents a brief description of smallholder agriculture in Ethiopia. We then discuss the data and descriptive statistics in section 5.3. Section 5.4 provides the conceptual and empirical models of the price expectation objective, and the respective econometric results. Section 5.5 presents and discusses the theoretical and empirical models, and the econometric results for the price prediction accuracy of farmers. Finally, section 5.6 provides the conclusions.

5.2. Smallholder agriculture in Ethiopia

By and large, agriculture in Ethiopia is dominated by smallholder farming.[26] Smallholder agriculture contributes about 95% of the total agricultural production and 85% of total area under cultivation in the country (CSA, 2010; Salami et al., 2010). Smallholder farmers grow various crops both for own consumption and for market supply. Cereals are the most commonly produced crops by smallholders in Ethiopia covering close to 80% and 85% of the total grain

[26]A smallholder in our context is defined as farming household with a landholding of less than 2 hectares.

crop area and production respectively (CSA, 2012a). *Teff*[27], corn, sorghum, wheat and barley are the dominant cereal crops cultivated in a wide range of agro-ecological zones of the country. While pulses and oilseeds are the other crops cultivated by smallholder farmers, smallholders' participation in the horticulture sector is quite limited.

Although they produce a majority of the food commodities in the country, smallholder farmers in Ethiopia have subsistence livelihoods. Several factors are argued to explain the low productivity and limited market surplus of smallholder agriculture in the country. Poor productivity due to lack of access to information, market, credit, and low adoption of modern agricultural technology is the long-standing challenge of smallholders in the country. For instance, in 2009/2010 main cropping season, only 44% and 12% of the farmers applied chemical fertilizers and improved seeds, respectively (Abebaw & Haile, 2013). Some also argue that small and fragmented landholding in the country limits intensification of smallholder agriculture and is a key constraint for the low farm income (Gebreselassie, 2006). The average farm size of smallholders in Ethiopia is less than a hectare and this is further fragmented into an average of 2.3 plots (Ibid.).

Another feature of the Ethiopian smallholding agriculture is that it is predominantly rain-fed. Due to lack of capacity, agricultural technology and infrastructure, irrigation is only minimally practiced by smallholder farmers in the country. Some studies indicate that only 5% of the cultivated area in the country is irrigated (Awulachew et al., 2007). As a result, the amount, timing and variability of rainfall are crucial for good agricultural productivity in the country. Rainfall is the commonly observed exogenous phenomenon that represents one of the main sources of information about future production in Ethiopia (Osborne, 2004). The government attempts to disseminate rainfall forecasts from several stations to rural farmers for early warning purposes and to assist them in their production decisions.

There are two production cycles in the country and harvest in each of the seasons greatly relies on the amount and onset of rainfall. Deficient or excessive as well as early or delayed rainfall during these two harvest seasons can lead to significant production failure. The main "meher" season, which accounts for about 95% of the country's private sector grain production, refers to

[27]*Teff* is a fine grain that predominantly grows in Ethiopia and is an important staple food in the country. Having colors that vary from white and red to dark brown, *teff* has an excellent balance of amino acids, and it is also high in protein, calcium, and iron.

the longer production cycle of which planting takes place mainly between May and June and harvesting is between November and January. Planting and harvesting of the secondary "belg" season take place between February to April and June to August respectively. Table 5.1 below illustrated the crop calendar of major cereals grown in Ethiopia.

The production seasons as well as land and other agro-ecological requirements of corn and sorghum make them competing crops both for land and other inputs. The growing period for corn and sorghum is longer compared to the other cereals, implying that the lean season for households growing these crops is much longer. Wheat and barley do also typically compete for land and inputs whereas *teff* is more labor intensive and requires a slightly more wet land before planting. Thus, the planting and harvesting seasons matter to identify the relevant output price information in the production decisions of farmers for each of the crops they produce.

Table 5.1. Crop calendar for major cereals in Ethiopia

Crop/*Month*	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*
Teff						■	■	■			▒	▒
Wheat						■	■				▒	▒
Corn			■	■	■					▒	▒	▒
Sorghum			■	■	■					▒	▒	▒
Barley					■	■				▒	▒	▒
All cereals("belg")		■	■	■		▒	▒	▒				
	■	*Planting*			▒	*Harvesting*						

Source: FAO GIEWS

Figure 5.1 shows how close planting prices are to harvesting prices, which are indicative of how good a naïve farmer who bases his expectations on current sowing prices can potentially predict upcoming harvest period prices. One can observe that planting period output prices are mostly good indicators of harvest period prices. This is especially true for *teff* but less so for sorghum. Figure 5.1 also shows that the significant rise in the nominal harvest period prices of all the four cereals within the twelve months from December 2007 to December 2008 was already apparent in the price changes between the corresponding planting months. For instance, the harvest-period *teff* price nearly doubled between 2007 and 2008 whereas that of corn increased by about 80% over the same period (in nominal terms). The corresponding planting period prices more than doubled between these seasons. Such large price variations between two consecutive harvest seasons hint that planting time output prices may be taken as more relevant price information for price expectation formation than previous harvest period prices.

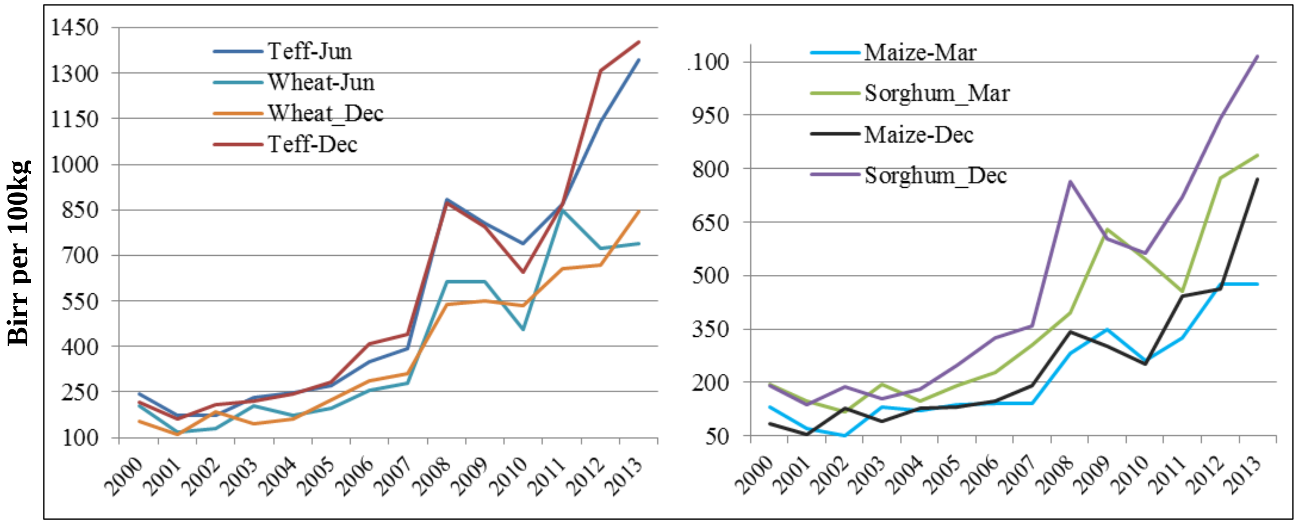


Figure 5.1. Planting and harvesting month nominal wholesale prices of major cereals, 2000–2013

Source: FAO GIEWS and Ethiopian Grain Trade Enterprise (EGTE)

The benefit for rural farmers of higher output prices depends on the marketable surplus they produce and take to nearby grain markets. Coupled with the limited surplus output, high transaction costs and inadequate market information limit the commercialization level of rural farmers. Although there exists variation across different regions of the country, commercialization of smallholder farmers is generally limited. Table 5.2 shows that about 20% of smallholder grain production is marketed whereas above 60% is used for home consumption. The remaining is set aside for seed or used as animal feed and for in-kind-payments.

Table 5.2. Crop utilization by smallholders in Ethiopia (2002/2003)

Crop	Utilization (%)		
	Consumption	Sale	Seed and others
Grains	64	20	16
Cereals	67	16	17
Oilseeds	61	22	17
Pulses	34	54	12

Source: Central Statistical Agency (CSA), Ethiopian Agricultural Sample Survey

Pulses are cultivated by smallholders mainly for market followed by oilseeds. However, smallholder production of these groups of crops is not as sizable as that of cereals of which households have the lowest marketable surplus. The awareness that is being created by the agricultural extension agents and lower transaction cost following the government's infrastructure investments are likely to change this situation in the near future. Better information about relevant output and input prices can foster the commercialization of farmers in the country. The price that farmers potentially receive for their output in the upcoming harvest season matters for their input application today. This, in turn, affects the productivity and future livelihood of the households.

Some may argue that higher output prices are not beneficial for net-buyer farmers, and they may actually prefer lower prices. In this line of arguments, net-buyers need not invest in acquiring information selling prices. Others might also argue that self-sufficient farmers need not care about output price information. Nevertheless, nearly all farmers take some of their produce to the market at some point in a year although most of them end up being self-sufficient or net-buyers for the whole year. Farmers' positions as a net-seller or a net-buyer vary from season to season and whether we measure the sell or purchase in terms of volume or in monetary terms. Thus, price information is crucial and smallholder farmers invest to acquire more and better information.

5.3. Data and some descriptive statistics

Data for this study come from a primary survey of rural smallholders from seven villages out of four different districts of Ethiopia, namely Kersa, Shashemene, Ada'a and Debre Birhan Zuria. Adele Keke is the *kebele*[28] selected from Kersa district and households in this village trade with adjacent towns of Dire-Dawa, Harar and Aweday in the Eastern part of the country. Smallholders in this area produce both staple crops typically corn and sorghum and cash crops like *chat*[29] and potato. Households were also interviewed from four adjacent villages from the Debre Birhan Zuria district, which is 120 kilometers northeast of Addis Ababa. The town of Debre Birhan is the nearby market for their livestock and grain production that typically consists of barley, wheat and horse beans among others. Sirbana Godeti is the other village where a sample of 78 households was interviewed and is the major supplier of *teff* to the surrounding and Addis Ababa

[28] A *kebele* is the smallest administrative unit in Ethiopia
[29] *Chat* is a perennial cash crop and a mild stimulant that is commonly used in the southern and eastern parts of Ethiopia.

markets. Having relatively more fertile soil, smallholders in this area also produce several leguminous crops and vegetables. Finally, we interviewed households from Turfe Ketchema, which is a village situated about 12 kilometers northeast of the town of Shashemene where they conduct most of their marketing with. The main crops that they produce for consumption and cash include potatoes, corn, wheat, barley and *teff*. Figure 5.2 depicts the fifteen villages selected for the Ethiopian rural household survey (ERHS) that started since 1989 (Webb et al., 1992), and the arrows indicate the survey sites of this particular study.

The survey was conducted from April-May, 2013 on a total of 415 households that were randomly selected from each village through stratification techniques.[30] The survey was conducted immediately before or at the onset of planting for the main "meher" season and that helps us to obtain good information on planting time prices. Furthermore, the dataset provides detailed information on household demographics, asset holdings, production and consumption, purchases and sales, seasonal prices, information sources, among others.

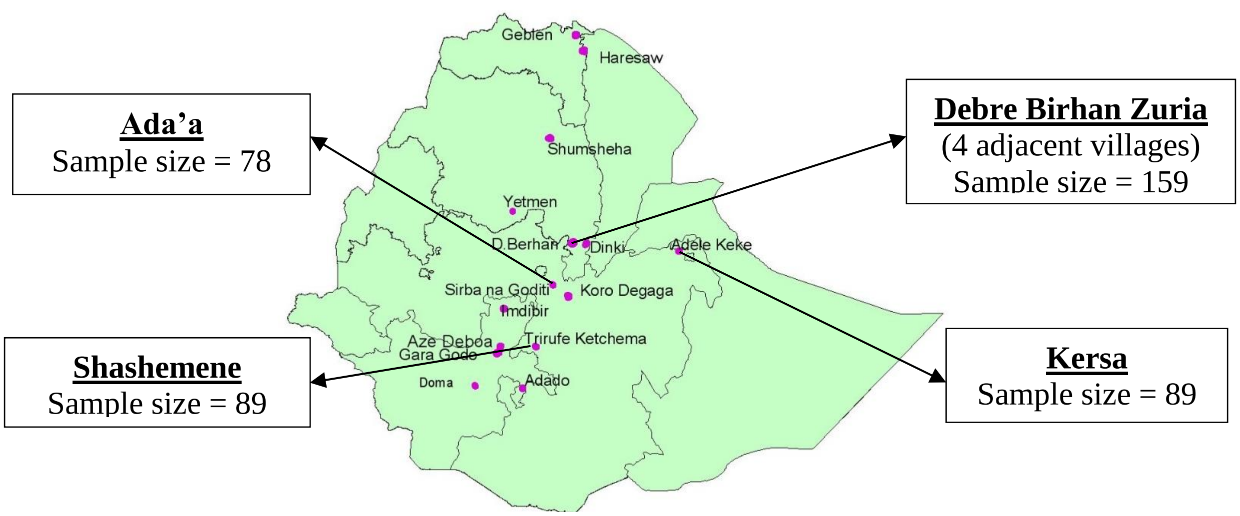


Figure 5.2. Ethiopian rural household survey villages

Source: Adapted from Dercon and Hoddinott (2011)

Following the liberalization of markets in Ethiopia in the early 1990s, prices have not only served as incentives to produce more but they have also become less predictable. Consequently, recent volatile food prices have posed additional challenges for farmers in their production

[30] The households in our sample were those selected for the EHRS rounds and detailed information on sampling techniques can be found from Dercon and Hoddinot (2004).

decisions. Information regarding input and output price developments, weather conditions, input availability and the like are hence crucial for the farmer to make a better production decision. From the primary survey in rural Ethiopia, we observe that most of the smallholder households report prices as highly unpredictable.

While 85% of the households suggest that output prices are likely to increase in the next one year, the other 11% said that prices are likely to decline. Although most of the farmers (87%) report that output prices after a year are more likely to be in the range of decreasing by half or increasing twice the amount they predicted, the remaining households report that prices are so unpredictable and they could be outside this range (Table 5.3). For these and other reasons, many of the households set a high price level to enter in contract farming. Although contract farming prices are typically lower than the average expected harvest time price as they include a risk premium, about two-third of the households in our survey areas are willing to accept contract-prices that are only equal or greater than their price expectations.

Table 5.3. Perception of farmers regarding the predictability of output prices

Item[31]		Proportion of households (%)
Output price prediction (in 1 year)	Increase	85
	Decrease	11
	Remain the same	3
	I don't know	1
Likelihood of price changes as compared to expectations	≥ Twice as high (H)	10
	≤ Half as low (L)	3
	In between L & H	87
Contract-farming price	> Expected price	35
	= Expected price	31
	< Expected price	31
	I do not know	3

Source: Own survey data, 2013

These farmers form their price expectations based on their information access. We asked them two similar but subtly different questions regarding their sources of price information. First, we wanted to know what the major sources of information for the market prices of their products are. Second, we asked them a more specific question with regard to what information they observe to predict the harvest-time price of their crop choice for cultivation. Figure 5.3 below

[31] The respective survey questions are available in the Appendix (II-A)

shows the major responses of the households. There are three major sources of price information for rural households in Ethiopia. While most of the smallholder farmers (54%) visit close-by markets to sell or buy products and thereby gather information about prices of their interest commodities, about 45% of them get price information from their fellow farmers. Although about two-third of the households own either a radio (57%) or a television (8%), it is only a quarter of the rural households that reported radio or television as sources of output price information. This may be because of lack of awareness about the exact times when price information is transmitted. The descriptive statistics also indicate that the Ethiopian commodity exchange (ECX) has not done enough to reach out rural smallholder farmers with price information.

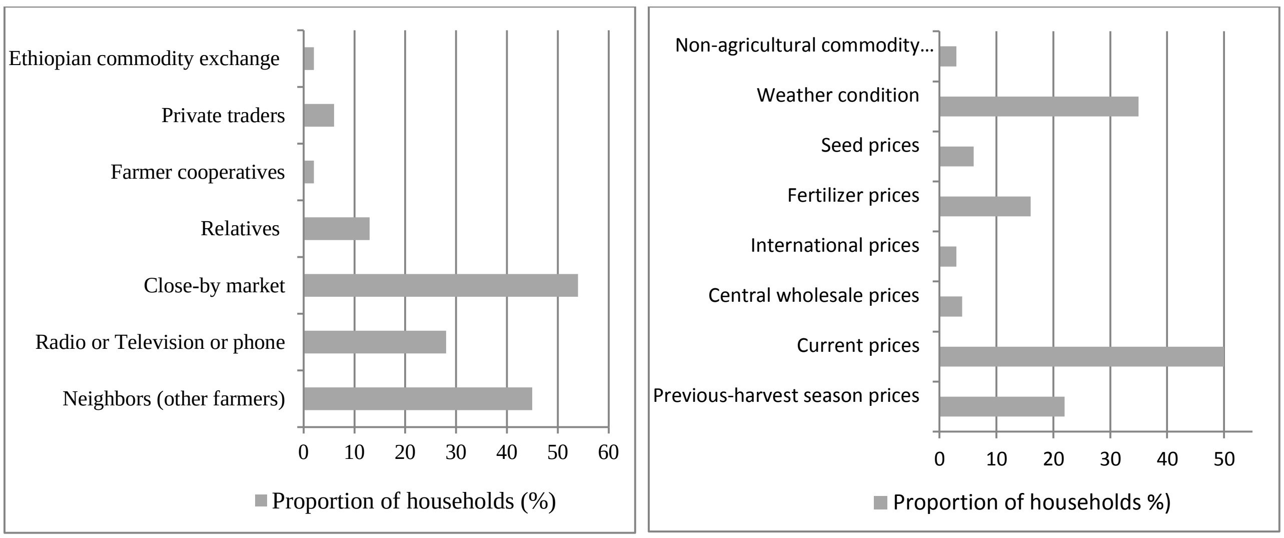


Figure 5.3. Primary source of price information (left) and relevant information for price expectation formation of smallholders (right)

Note: respondents were allowed to give multiple responses

Source: Own survey data, 2013

It is also interesting to see that about half of the smallholder farmers form their harvest-time price expectations based on the currently available price information. About a fifth of the respondents also consider past harvest period prices in their price expectation formations. This may suggest that these households form their price expectations in line with the adaptive or naïve price expectation formation hypothesis. This is consistent with a finding by Chavas (2000) who also found that close to half of the US beef markets were associated with the naïve expectation hypothesis. Nevertheless, other information such as weather, input prices and central wholesale prices are reported as relevant information in the process of price expectation formation of the smallholder farmers. The information sources for households vary depending on their market access and ownership of assets among other things. It is less likely for remote farmers to go to town markets to gather price information and they may be more likely to depend on information from their neighbors or from radio.

Subject to their access to information and their ability in data processing, the smallholder farmers make their price predictions for the next harvest period. These also matters for the quality of their price expectations. The better access farmers have to relevant price information, the more precise their price predictions will be. This is, however, an empirical question to understand what explains the precision in their price expectations. This is important since better price expectations result in a more efficient allocation of resources in production. Table 5.4 presents the descriptive statistics of the smallholders in our survey sites, highlighting the household characteristics, asset holdings and other variables that could potentially affect the farmer's data gathering and processing that are, in turn, important for better expectation formation.

The summary statistics in Table 5.4 show a lot of similarities among the households from the four survey districts. On average, the household heads are in their mid-50s and greater than two-third of them are married and male. The average family size (6.1) is slightly greater than the average size in rural Ethiopia, which is 5.1 according to the household consumption and expenditure survey in 2010/2011 (CSA, 2012b). The average family size is higher for households in Kersa district followed by those in Shashemene. Although about 55% of the overall household heads have some literacy from formal or informal education, it is only the second grade that the average head has completed. The total land owned by the smallholders is about 1.68 hectares: while smallholders in Debre Birhan district have, on average, slightly greater than 2 hectares those in Kersa have slightly less than a hectare of land. The average per capita farm size is less than half a hectare.

Besides the above household characteristics, ownership of information assets such as mobile, radio and television are very important in obtaining market, rainfall and other information that could improve households' production decision. Although it is less than a tenth of the smallholders who own television, about 80% of them have access to information.[32] Other indicators of access to market and information include distances from basic facilities. For instance, smallholder farmers live close to an average of 3 and 10 kilometers away from an all-

Table 5.4. Summary statistics of sampled smallholders by district

District		***Debre Birhan***		***Ada'a***		***Kersa***		***Shashemene***		***Total***	
Variable		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Household characteristics											
Age of head		55	15.34	59	15.21	52	15.20	52	18.05	54	16.05
Female headed HH (%)		30	0.46	31	0.46	35	0.48	29	0.46	31	0.46
Married HH head (%)		64	0.48	65	0.48	69	0.47	79	0.41	68	0.47
Family size		5.41	2.07	5.50	2.13	7.27	3.02	6.54	3.25	6.07	2.69
Years of schooling		1.36	2.56	1.75	2.92	1.24	2.16	3.65	4.43	1.90	3.18
Leadership position (%)		25	0.44	13	0.34	15	0.36	20	0.40	20	0.40
Asset ownership											
Total farm size (ha)		2.39	0.78	1.62	0.84	0.96	0.62	1.18	0.63	1.68	0.94
Per capita farm size (ha)		0.51	0.32	0.32	0.22	0.17	0.16	0.22	0.17	0.34	0.29
Radio ownership (%)		62	0.49	53	0.50	48	0.50	63	0.49	57	0.50
Television ownership (%)		1	0.11	23	0.42	4	0.21	12	0.33	8	0.28
Mobile ownership (%)		62	0.49	71	0.46	73	0.45	63	0.49	66	0.47
Oxen ownership (%)		86	0.35	73	0.45	16	0.37	58	0.50	63	0.48
Tropical Livestock Unit (TLU)[33]		9.60	4.83	5.00	3.53	2.35	1.48	2.79	2.20	5.85	4.83
Household asset (index)		0.70	0.64	0.02	0.79	-0.89	0.82	-0.38	0.94	0.00	2.45
Farm income share (%)		99	0.8	97	0.15	98	0.10	99	0.01	98	0.10
Market surplus (%)		2	0.80	18	0.16	1	0.03	30	0.22	11	0.18
Access to market and information											
Access to information (%)		80	0.40	81	0.40	79	0.41	80	0.40	80	0.40
Distance to nearby grain market	km	10.36	3.11	11.45	1.61	6.81	3.33	8.73	3.65	9.46	3.47
	hr	2.05	0.62	2.28	0.49	1.73	0.95	1.64	0.82	1.94	0.76
Distance to dry weather road	km	2.48	2.25	0.52	0.78	0.58	0.56	0.85	1.18	1.41	1.84
	hr	0.55	0.49	0.13	0.15	0.17	0.19	0.25	0.30	0.33	0.40
Distance to all weather road	km	3.42	2.63	1.06	1.03	1.39	1.81	2.79	2.07	2.41	2.33
	hr	0.69	0.47	0.25	0.21	0.33	0.25	0.62	0.42	0.51	0.42
Distance to development extents' office	km	4.16	3.13	3.02	1.54	1.77	4.82	12.28	86.92	5.16	40.20
	hr	0.92	0.61	0.70	0.48	0.39	0.32	0.36	0.35	0.65	0.54
N		159		78		89		89		415	

Source: Own survey data, 2013

[32] Access to information here is defined as ownership of any of the three assets namely, radio, television or mobile.

[33] A Tropical Livestock Unit (TLU) is an animal unit used to aggregate different classes of livestock. The standard used for one TLU equals an animal of 250 kg live weight. Different formulae are used for estimating TLU depending on the typical livestock varieties and geographical contexts. In this study, we use 1 TLU to refer to 1 ox/cow, 0.75 bull/heifer, 0.45 calf, 0.15 goat/sheep, 0.5 donkeys, 1.15 horse/mule, 1.5 camel and 0.005 for poultry (Adapted from Ramakrishna & Demeke, 2002).

weather road and a nearby grain market respectively. Thus, the average household head needs to walk about 1 and 2 hours to access these facilities respectively.

As agriculture is the main activity in all these four districts, it is not surprising that off-farm income contributes less than 2% of the households' incomes. Market surplus, as measured by the share of output sale from total production, is negligible in Kersa and Debre Birhan districts. This is mainly because *chat* is the main cash crop in Kersa and sale of livestock is common in the latter.[34]

The secondary data for our analyses including central wholesale prices and international prices are obtained from the FAO GIWS and World Bank price databases, respectively. Historical rainfall data are obtained from the national meteorology agency (MNA) of Ethiopia.

5.4. Price Expectation formation of smallholder farmers

5.4.1. Conceptual framework

A basic economic supply model explaining production of a certain crop is formulated as a function of its own and competing crops' harvest-time prices and other exogenous factors. Nevertheless, the harvest time prices are not realized during the time of input allocation and producers need to make their price expectations. Thus, a simple supply response model of a given crop at time *t* can be specified as:

$$Q_t = \beta_1 + \beta_2 p_t^e + \beta_3 Z_t + u_t \tag{5.1}$$

where Q is the desired output or acreage in period t, p_t^e is a vector of expected prices of the crop under consideration and of other competing crops, Z is a set of other exogenous variables, u_t accounts for unobserved random factors affecting crop production. Hence, there is an underlying price expectation that the economic agents make and the supply response modeler should make a hypothesis of.

[34] We calculate the market shares based on total sale and production of six crops, namely *teff*, wheat, corn, sorghum, barley and horse beans to be consistent with our empirical analysis

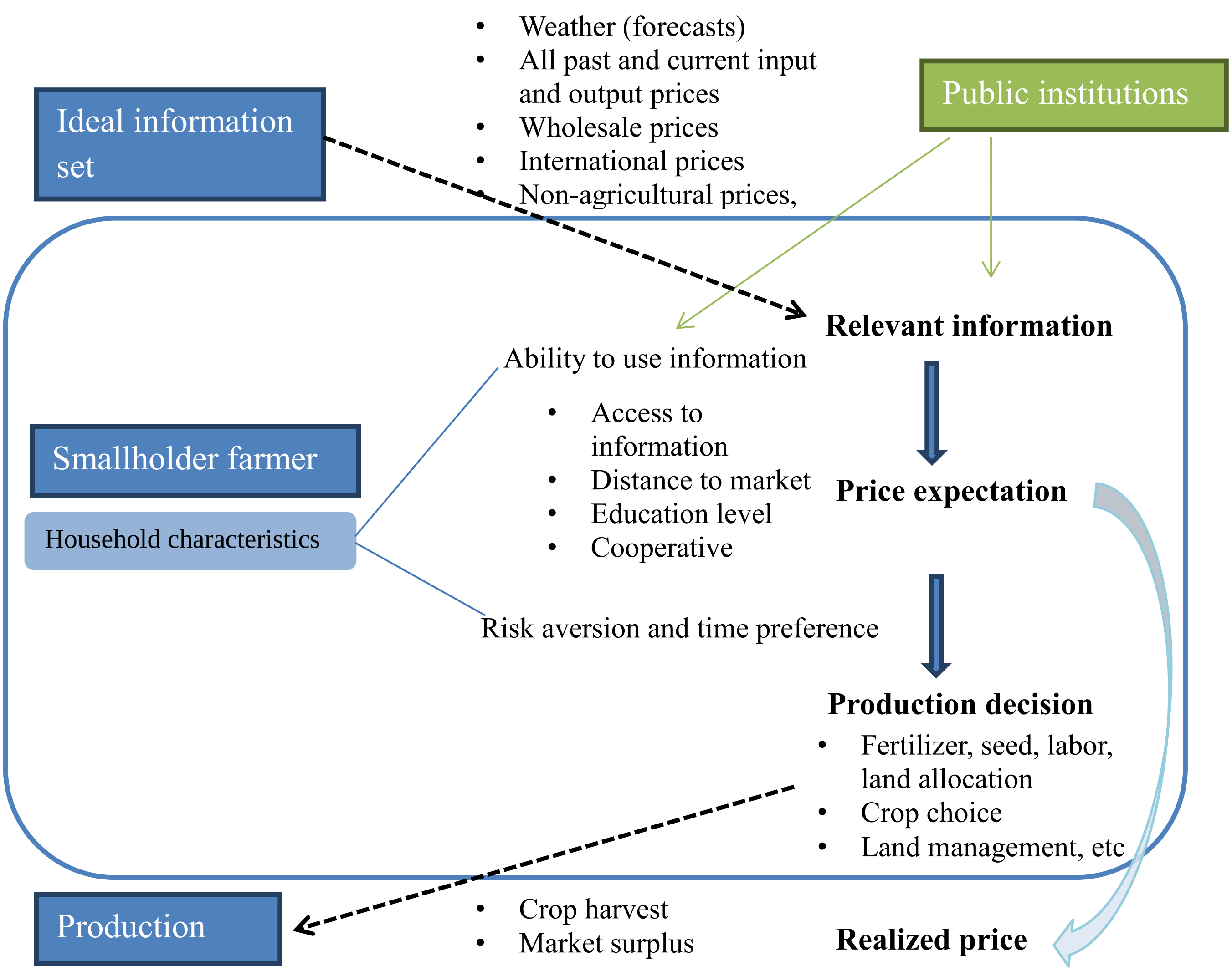


Figure 5.4. Conceptual framework, own illustration

Source: Own illustration

There is little agreement among applied researchers regarding any a priori superior specification for price expectation (Shideed & White, 1989). The price expectation formation of economic agents depends on several factors and Figure 5.4 illustrates some of the factors that potentially constitute the relevant information set in the context of smallholder farmers in a typical developing country. The smallholder gathers information from several sources about, among others, previous and current output prices, input prices and weather conditions. The farmer then processes the gathered information and makes his expectations about the likely price of his crop choice during the next harvest period. This data processing stage and the degree of accuracy in forecasting the harvest-time prices, however, depends on asset and household characteristics, level of education and risk perception of the smallholder farmer among others. Depending on this expected price, the smallholder farmer then decides how much fertilizer, labor, acreage, and land management to allocate for each crop.

In general, the expected price in the supply model above can be specified as:

$$p_t^e = f\left(p_{t-p}, w_{t-p}, r_t, Z_t\right) \tag{5.2}$$

where p_{t-p} and w_{t-p} refer to current and previous output and input prices, r_t refers to actual sowing time and expected growing time rainfall quantities, and Z_t denotes other exogenous variables that could potentially explain expectations. The above function is general and it allows different price expectation hypotheses depending on what information we include in the function. If expectations are assumed to be formed in line with the rational expectation hypothesis, an autoregressive moving average model of output prices should be estimated after substituting the price expectations function in the supply model. A quasi-rational expectation hypothesis, on the other hand, generates a one-step price forecast and uses these prices as data in the supply response model in equation (5.1) above (Shideed & White, 1989). Similarly, the naïve expectation model equates the expected price with the market price in the previous year whereas in the futures price model the price associated with a futures contract at harvest is used to proxy price expectations.

For instance, as it is typical in the literature, a quasi-rational expectation can be formulated using an error-correction time series model. Suppose $\boldsymbol{x}_{t-1}$ represents a set of exogenous variables that smallholders use in predicting their output prices, p_t^e a quasi-rational forecasting regression can be written in the form of an error-correction model:

$$\Delta p_t^e = \alpha \Delta x_{t-1} + \rho z_{p,t-1} + \varepsilon_t \tag{5.3}$$

where $\rho z_{p,t-1}$ is the long-run relationship between the dependent variable and the explanatory variables with ρ as the cointegrating term. After estimating equation (5.3) with ordinary least squares, fitted values can then be used to represent the economic agents' price expectation in equation (5.1) above.

5.4.2. Empirical model

Most of the theoretical model and empirical applications of price expectation formation are in the context of a time series analysis (Holt & McKenzie, 2003; Nerlove & Fornari, 1998). This is due to the fact that we do not know the harvest-period prices and we would like to forecast or predict them based on past price realizations. Hence, the researcher hypothesizes a model what he or she thinks best represents the agent's expectation formation. In this study, however, we obtain the expected prices of the smallholder farmers from the primary survey. Thus, we need not to forecast or predict a price that is supposed to represent the agent's expectation. Instead, we identify the factors that enable the agent to come up with the reported expected price.

There are five major cereals, namely *teff*, wheat, corn, sorghum and barley, and a common leguminous plant in the context of Ethiopia, horse beans, for which we gather expected price information from smallholders.[35] In general, the expected price of the i^{th} household for a given crop c at sowing time $(t = s)$ can be specified as:

$$p^{e}_{ic,s} = \alpha_0 + \sum_{t=h,s} \alpha_j \, p_{ic,t} + \sum_{t=h,s} \beta_j \, p^{cw}_{c,t} + \sum_{t=h,s} \gamma_j \, p^{I}_{c,t} + \theta_i w_{i,s} + \sum_{t=s,g} \eta_j \, r_{ic,t} + v_{ic,s} \quad (5.4)$$

where h, s and g refer to the previous harvest, the current sowing and growing seasons respectively. The second term on the right side, for instance, refers to previous harvest and current planting period output prices, both obtained from the survey. The superscripts cw and I denote central wholesale output prices and international output prices. w refers to variable input expenditure, which consists of expenses on fertilizer, pesticides, hired labor, purchased seed and renting oxen. Since expenditure on these inputs is known to farmers at planting time depending on their prices and the amounts they purchase, we consider planting time expenditure only. Planting as well as growing period rainfall, r also affects price expectations. Finally, $\alpha, \beta, \gamma, \theta$ and η are parameters to be estimated and v is the error term.

The dependent variable, $p^{e}_{ic,s}$ is obtained from a primary survey where farmers, at sowing time, were asked to report their expected prices for each crop for the next harvest season. Moreover, farmers were asked regarding their knowledge of crop prices at the previous harvest season and

[35] Horse beans is usually sown from mid-June to first week of July and harvested from end of October to November.

at the current sowing period, referring to $p_{ic,h}$ and $p_{ic,s}$ in equation (5.4). We also construct harvesting and sowing period crop prices using wholesale prices from the Addis Ababa market, $p_{c,h}^{cw}$ and $p_{c,s}^{cw}$ and international output prices, $p_{c,h}^{I}$ and $p_{c,s}^{I}$. The wholesale and international prices obviously vary across crops. Moreover, these seasonal prices have some degree of variation across farmers depending on the planting and harvesting seasons of the crops that the farmer grows. We could use international output prices as alternative or additional to the central wholesale prices. However, since it is only 2% of the smallholders that reported international prices as relevant information in their expectation formations and since some crops (e.g. *teff*) are not traded in the international market, we opt to use only the domestic wholesale prices in our empirical model. This is also important to reduce multicollinearity problem among explanatory variables in the regression.

The rainfall variables, $r_{ic,s}$ and $r_{ic,g}$ refer to sowing and growing period rainfall amounts in millimeters. While the former is the actual amount of rainfall, the latter refers to smallholders' rainfall expectations for the upcoming growing months of their crops. $r_{ic,s}$ is, therefore, the amount of rainfall from nearby meteorological stations at the sowing period of each crop. Similarly, the average growing period amount of rainfall over the previous five years is used as proxy for farmers' rainfall expectations for the coming growing season. The rainfall variables vary across households since rainfall varies across the four diverse geographical study areas. Besides, we multiply the sowing time rainfall by the dummy of rain included in the questionnaire, in which smallholders were asked if sowing time rainfall was enough and on time. This is important as it is not only the amount of the rainfall at the village level that matters but also the timing and amount of rainfall with respect to the individual farmer's crop. The rainfall variables also vary across crops depending on the planting and growing months of each crop (Table 5.1).

Table 5.5 provides the summary statistics of the variables that are used in the estimation of the price expectation model. One can see that the planting period prices are, on average, higher than the previous harvest prices for all crops. This is a typical reflection of the seasonality of agricultural markets where most smallholders with little storage capacity take their output to the market immediately after harvest. This is consistent with the anecdotal evidence that liquidity-constrained smallholder farmers, in general, tend to sell their crops immediately after harvesting, and with studies that indicate similar patterns for Ethiopian farmers (Osborne, 2005).

Table 5.5. Descriptive statistics of the variables used in the expectation model, by crop

Crop	*Teff*	Wheat	Corn	Sorghum	Barley	Horse beans
Variable	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*
Expected price	1441 (307)	690 (135)	575 (131)	707 (168)	568 (125)	698 (158)
Previous harvest price	1320 (228)	652 (102)	525 (86)	644 (117)	553 (100)	670 (136)
Sowing price	1516 (167)	726 (95)	586 (66)	704 (125)	622 (85)	726 (144)
Sowing rainfall (mm)	128 (34)	128 (36)	82 (35)	82 (36)	128 (34)	128 (34)
Growing rainfall (mm)	171 (77)	171 (87)	193 (78)	193 (76)	171 (77)	211 (106)
Input expenditure (Birr)	1040 (1793)	1008 (1030)	186 (312)	283 (366)	2017 (1623)	381 (615)
Previous harvest wholesale price	1309 (0)	667 (0)	461 (0)	942 (0)	500 (0)	1100 (0)
Sowing wholesale price	1343 (0)	738 (0)	474 (0)	839 (0)	700 (0)	1000 (0)
Previous harvest world price	-	643 (0)	573 (0)	521 (0)	451 (0)	-
Sowing world price	-	570 (0)	542 (0)	516 (0)	431 (0)	-
Prediction error (%)[36]	20 (9)	19 (9)	19 (10)	19 (11)	20 (10)	19 (01)
Number of observations	172	313	213	133	188	168

Note: All prices are in Ethiopian Birr per 100 kg.[37] The international prices are average of sowing and harvesting month prices.

Source: Own survey data, 2013

The smallholders' expected price for the next harvesting period is, on average, in between the previous harvest and current sowing prices for nearly all crops. This conclusion remains unchanged even after adjusting for inflation with the average national Consumer Price Indices (CPI) in the respective periods. Given that barley is mainly grown in the Debre Birhan Zuria district where the land is highly degraded, smallholders spend the highest amount of money on

[36] This is the relative deviation of farmers' expected prices from the actual crop prices that are observed in the local markets at harvest time for which expectations were made.

[37] Average official exchange rates during the harvesting and planting periods are used to convert international prices to local prices: the respective figures are of 18.07 and 18.42 Birr per US Dollar respectively.

variable inputs, mainly for fertilizer. Besides barley, *teff* and wheat have relatively higher fertilizer and other variable input requirements. The rainfall amount is typically lower during the sowing period compared to the growing period for all crops.

We can pool the data across the six crops and the above model can be estimated using pooled ordinary least squares (OLS). However, unobserved heterogeneities across households such as ability in gathering and processing data affect price expectation, which potentially causes endogeneity problem in the OLS estimation. Such heterogeneities are, however, constant across crops that a farmer grows. We can get rid-off such unobserved heterogeneities in a fashion similar to the fixed-effects panel data framework. The Hausman test indicates that these individual heterogeneities are correlated with the independent variables and estimates will be biased if they are left in the error term. Alternatively, we use prediction error of smallholders to proxy some of such unobserved heterogeneities.

5.4.3. Results and discussion

Table 5.6 presents the econometric results for the expectation model in equation (5.4). The first two columns report results from OLS regressions for comparison purpose. In the second column, we use price prediction errors of smallholders as proxy for the unobserved heterogeneities described above[38]. Since there are indications for the endogeniety of variables in the expectation model and the proxy may not fully capture these variables, we preferred estimations from the *FE-like* regressions. The results of the expectation model from our preferred estimations show that each of the statistically significant regressor variables has the *a priori* right sign, which is consistent with standard economic theory. The values of the R^2 in Table 5.6 are also informative of the good fit of the estimated models.

Focusing on results from the *FE-like* model, farmers tend to have a higher price expectation for the next harvest period if they observe higher local market output prices at the previous harvest and current sowing periods. More specifically, a 100 Birr increase in each of these output prices – in nominal terms – adds about 50 Birr into the farmer's price expectation, ceteris paribus. Similarly, farmers tend to have higher price expectations if they observed higher wholesale prices at the central market in the previous harvest period. However, the smallholders care little

[38] Discussions and definition of the prediction error is in order in subsequent sections of this chapter.

about the wholesale prices in the capital market at the time of sowing and, if it all, it has a negative effect. This may be because these farmers are predominantly subsistent and do not have surplus produce that lasts until the next sowing period. They take their crop production to markets typically after the harvest period in order to pay loans, which they borrowed to purchase fertilizer and other inputs at planting time. This is a typical feature of liquidity constrained smallholder farmers in many developing countries (Osborne, 2005). Although about a third of the smallholder farmers applied chemical fertilizer for at least one of their cultivated crops, input expenditures do not statistically affect farmers' price expectations.

Table 5.6. Expectation model results

Dependent variable: Farmer price expectation			
	OLS	OLS-Proxy	*FE-like*
Prev. harvest price	0.42***	0.44***	0.46***
	(0.06)	(0.06)	(0.07)
Sowing price	0.58***	0.56***	0.49***
	(0.05)	(0.06)	(0.06)
Sowing rainfall	0.36*	0.33	-0.29
	(0.15)	(0.2)	(0.89)
(Expected) growing rainfall	-0.02	-0.03	-0.62**
	(0.06)	(0.08)	(0.28)
Prev. harvest wholesale price	0.12**	0.14**	0.09*
	(0.05	(0.05)	(0.05
Sowing wholesale price	-0.13	-0.15*	-0.05
	(0.07)	(0.07)	(0.06)
Input expenditure	-0.003	-0.001	-0.001
	(0)	(0)	(0)
Prediction error		2.72***	
		(0.78)	
Intercept	1.36	-47.54*	84.10
	(18.13)	(21.66)	(51.64)
Adj. R^2	0.80	0.81	0.89
N	1187		

Notes: Robust standard errors adjusted for household clusters are in parentheses. ***, **,* denote statistically significance a 1%, 5% and 10% levels respectively.

Rainfall is another important factor that affects smallholders' price expectations. Both sowing and growing period rainfall have an expected negative sign, implying that farmers lower their expected prices following good rainfall conditions. Since the rainfall variable is adjusted both by its timing and amount, it reflects the appropriate rainfall for a better production in that particular season.

We have done alternative specifications of our preferred model. In order to understand whether previous harvest or current sowing period prices are more relevant in the price expectation formations of smallholders, we exclude either of these variables in our *FE-like* regression. This is important as the two price variables are correlated, with a partial correlation coefficient of 0.69. One can see from Table 5.7 that both price variables are equally important for price expectation formation of smallholder farmers. Nevertheless, including both price variables explains the variation in price expectations of smallholders better than including either price alone. And, if only one price is included, sowing price has a better explanatory power than harvesting price (due to its proximity to the next harvest).

Table 5.7. Alternative FE regression specifications

Dependent variable: Farmer price expectation					
	(1)	(2)	(3)	(4)	(5)
Prev. harvest price		0.87***		1.04***	0.48***
		(0.05)		(0.03)	(0.07)
Sowing price	0.82***		0.91***		0.51***
	(0.03)		(0.02)		(0.06)
Sowing rainfall	0.24	-0.49			
	(1.04)	(1.04)			
(Expected) growing rainfall	-0.92***	-1.35***			
	(0.3)	(0.33)			
Prev. harvest wholesale price	0.09*	0.01			
	(0.06)	(0.06)			
Sowing wholesale price	0.03	0.20**			
	(0.07)	(0.09)			
Input expenditure	-0.004	-0.003			
	(0.01)	(0)			
Intercept	106.62*	135.85**	41.09**	22.83	9.90
	(59.83)	(61.01)	(17.39)	(19.42)	(16.25)
Adjusted R^2	0.87	0.87	0.87	0.86	0.89
N	1187				

Notes: Robust standard errors adjusted for household clusters are in parentheses. ***, **,* denote statistically significance a 1%, 5% and 10% levels respectively.

Overall, the results are in line with producer expectation theory and with previous empirical work although, to our knowledge, no related previous work considers farmer-reported price expectations. The results show that farmers make use of other information in addition to previous harvest period output prices. This might hint that assuming smallholder farmers as naïve in their price expectations may not be appropriate. The results are consistent with previous empirical studies that applied quasi-rational forecasting models in order to fit producers' price expectations in Ethiopia (Getnet et al., 2011). Using monthly information from a surplus producing area in Ethiopia, Getnet et al. (2011) show that producer and wholesale prices are important factors in forecasting producers' expectations in the area.

5.5. The role of information

The second research objective of this chapter is to study the role that information plays in the price expectation formation of smallholder farmers in Ethiopia. Farmers involve themselves in gathering and processing price and other information, which they believe improves their price expectations. Thus, they need to invest in acquiring such information, which may be by purchasing information assets such as radio, television and phone or by paying for transportation to nearby markets. This process is costly for the individual farmer. Additionally, there is a certain level of externality in that the information a farmer obtains is a partially non-excludable public good that other farmers may use without paying. Accordingly, it might be necessary for the government to provide market information as public good through organized market information systems. However, we want to empirically test if investments on acquiring information actually improve the prediction accuracy of smallholder farmers in rural Ethiopia.[39] The following section develops a theoretical model that motivates the importance of information in improving the price signal for farmers.

5.5.1. Theoretical model

To better understand farmer's behaviour in deciding on the size of inputs and investments into acquiring information about prices that are likely to prevail during the harvest season, we develop a simple theoretical model. Suppose a typical farmer purchases inputs x at a constant unit cost c, which gives production $q(x)$ with the usual conditions $q'(x) = \frac{\partial q(x)}{\partial x} > 0, q''(x) = \frac{\partial^2 q(x)}{\partial x^2} < 0$.[40] As inputs need to be purchased during the planting period and revenues occur only

[39] We use the same dataset as described in the previous section, and we do not repeat the data section here.

[40] For the sake of simplicity, we consider here only the one-dimensional case of input decisions and abstract from crop choice and harvest uncertainty.

at the time of the harvest when production can be sold at price *p*, the discounted profit of the farmer is:

$$\pi(p) = -cx + \frac{1}{1+r} pq(x) \qquad (5.5)$$

with *r* being the discount rate (cost of capital). As harvest period prices are, however, uncertain during planting time and smallholder farmers are more likely to be risk-averse due to limited access to insurance markets, the farmer maximizes expected utility of discounted profits over the unknown price *p* but conditional on observed signals *z*, which contains some information on the price *p* that will be realized at harvest:

$$max_x\, E\{u[\pi(p)]|z\} \qquad (5.6)$$

The signal *z* can be understood as a composite of information on current and past prices as well as expected supply and demand conditions. We assume that farmers have rational expectations in the sense that they do not *systematically* misinterpret the signals *z* into one direction (either above or below the expected price *p*). Hence, without loss of generality we can set $z = p + \varepsilon$ with $E[z] = E[p]$ and $E[\varepsilon] = 0$. The signal will on average reveal the correct price but the realized price will be different by a random component ε. Substituting $p = z - \varepsilon$ into (5.6) gives:

$$\max_x E\{u[\pi(z-\varepsilon)]\} \qquad (5.7)$$

We further assume for simplicity that the noise of the signal ε is normally distributed with variance $h = Var(\varepsilon)$. The variance is directly related to the quality of the signal: A good quality signal will have a low variance (i.e. the realized price will be close to the price revealed by the signal) and a bad quality signal will have high variance. A key feature of this model is that farmers can invest into acquiring information that improves the quality of the signal and, hence, reduces the variance h. This is formalized by $h = h(I) \geq 0$ with $h'(I) < 0$ and $h''(I) > 0$. This implies that the variance (noise of the price signal) is a decreasing function of access to information but at a decreasing rate. Figure 5.5 illustrates this relationship with a convex to the origin curve, indicating that the rate at which the quality of the signal improves with more information is decreasing.

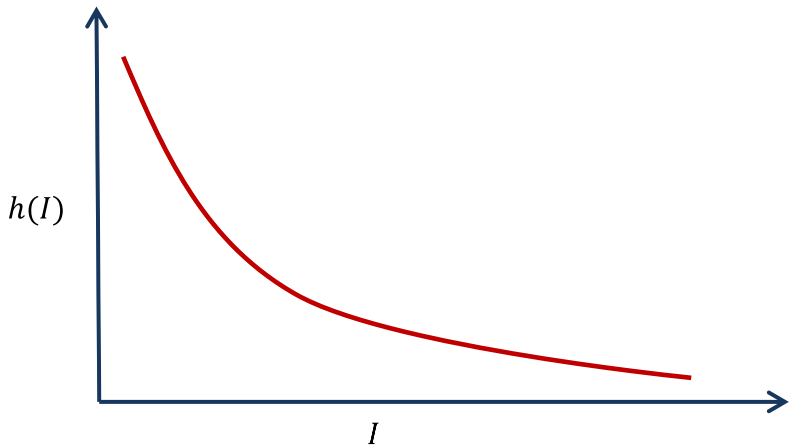


Figure 5.5. Relationship between level of information and the quality of the price signal

The profit function (5.5) becomes therefore:

$$\pi(z-\varepsilon) = -cx - kI + \tfrac{1}{1+r}(z-\varepsilon)q(x) \qquad (5.8)$$

with $Var(\varepsilon) = h(I)$, and where k is the unit cost of investing in acquiring information that accrues during the planting period. Applying an exponential utility function $u(\pi) = -\exp(-R\,\pi)$ where R measures the absolute risk aversion, the expected utility maximization problem of the farmer can be decomposed into a weighted sum of expected profits and the variance of profits, which is determined by the level of investments into information I:

$$\max_{x,I} E\left[u\left(-cx - kI + \frac{(z-\varepsilon)q(x)}{1+r}\right)\right]$$

$$= \max_{x,I}\left\{-cx - kI + \tfrac{zq(x)}{1+r} - \tfrac{R}{2}h(I)\left(\tfrac{zq(x)}{1+r}\right)^2\right\} \qquad (5.9)$$

In fact, equation (5.9) is similar to the mean-variance utility function where the certainty equivalent of the farmer's expected utility from farm profit is expressed in term of its first two moments of profit: expectation and variance (Coyle, 1992, 1999). More specifically, equation (5.9) can be rewritten as $E[u(\pi)] = \max_{x,I}\left\{E(\pi) - \tfrac{R}{2}h(I)\sigma_\pi^2\right\}$. The optimal allocation of inputs x^* and investments into information I^* is determined by the first-order conditions:

$$\tfrac{\partial E[u(\pi)]}{\partial x} = 0 = -c + \tfrac{zq'(x^*)}{1+r} - Rh(I^*)\tfrac{z^2q(x^*)q\prime(x^*)}{(1+r)^2} \qquad (5.10a)$$

$$\frac{\partial E[u(\pi)]}{\partial I} = 0 = -k - \frac{R}{2} h'(I^*) \left(\frac{zq(x^*)}{1+r}\right)^2 \tag{5.10b}$$

The optimality conditions reveal some important aspects: Farmers choose the optimal level of input and investments in acquiring information to increase profits and to reduce revenue risk. When farmers are risk-neutral ($R = 0$) the quality of the signal becomes irrelevant for the farmer's utility. Thus, optimal investment into information acquiring would be zero and the standard first-order conditions regarding the optimal level of inputs apply.

Considering just the optimality condition on inputs (5.10a), and ignoring (for the moment) that *I* and *h* are set optimally, reveals a complex response of optimal inputs (and thus production) to the quality of the signal:

$$\frac{dx^*}{dh} = -\frac{zqRx^*}{(1+r)(1-\alpha)+hRzq(2\alpha-1)} \tag{5.11}$$

where $\alpha = \frac{q'x}{q} < 1$ is the elasticity of the supply response to inputs. As direct implication of corollary 1 and 2 in Appendix II-B, a higher variance can lead to higher or lower input use and, thereby production, depending on the quality of the signal and the supply elasticity α: If the signal is not too bad (h is not very large) or if elasticity α is sufficiently large, a marginal improvement of the signal on the harvest price increases input use and, thus production. On the contrary, if the quality of the signal is bad (h is large) and production has a weak response to input use, a marginal improvement in the quality of the signal will lead to lower production.

Likewise, the optimality condition in (5.10b), again ignoring for the moment that *x* and *q* are also set optimally, gives:

$$\frac{dI^*}{dq} = -\frac{2h'(I^*)}{qh''(I^*)} > 0 \tag{5.12}$$

which implies that the higher the productivity of a farmer is, the more he will invest into acquiring more information to improve the quality of the signal. The reason is that the effect of price risk is larger for more productive farmers as they will have larger volume of production that otherwise will be affected by the risk.

Risk aversion

The latter phenomenon becomes also visible in the total derivative of the optimal investment in the risk parameter R (again, ignoring the simultaneous response of inputs from equation (5.10a)):

$$\frac{dI^*}{dR} = \frac{I}{R\beta} > 0 \tag{5.13}$$

where $\beta := -\frac{Ih'}{h} > 0$ is the elasticity of the variance to information. Hence, the more the absolute risk aversion of a farmer, the more he invests into the quality of the signal. The impact of the risk aversion of the joint optimum where equations (5.10a) and (5.10b) hold is ambiguous because inputs and investments simultaneously respond to a change in the risk aversion (see Proposition 1 in the Appendix II-B) in this case. Higher risk aversion can lead to higher or lower production and investments into information depending again on the elasticity of supply and the quality of the signal itself.

Cost of information

From the optimality condition (5.10a), we see that the cost of information *k per se* is irrelevant for the choice of the optimal inputs as

$$\frac{dx^*}{dk} = 0 \tag{5.14}$$

Regarding the investments into information, however, higher unit cost *k* leads to lower investments and thus, to a lower quality of the signal as the total derivative of (5.10b) after *k* is:

$$\frac{dI^*}{dk} = -\frac{2(1+r)^2 I^2}{(zq)^2 Rh\beta(1+\beta)} < 0 \tag{5.15}$$

In the joint optimum where both x^* and I^* adjust to changing costs of information, the sign is ambiguous and better information can increase or decrease production and signal quality depending on α and h (see Proposition 2).

Discount rate (cost of capital)

Regarding the role of the discount rate for applying inputs (and increase production) we find from (5.10a) that:

$$\frac{dx^*}{dr} = -\frac{(1+r-2hzqR)x}{(1+r)\Gamma} \tag{5.16}$$

In case of a risk-neutral farmer, $R = 0$ where Γ becomes always positive, implying the usual results that high discount rates or high costs of capital reduce input use and production as $\frac{dx^*}{dr} < 0$. In case of a risk-averse farmer, lower discount rates do not necessarily lead to higher input use and production as these could also increase the revenue risk. Considering the isolated impact of the discount rate on optimal investments in information we get

$$\frac{dI^*}{dr} = -\frac{2I}{(1+r)(1+\beta)} < 0 \tag{5.17}$$

which implies that lower discount rates lead to higher investments into information. In the joint optimum where both effects are considered simultaneously, the role of the discount rate is for both decisions ambiguous.

While the theoretical model sheds light into the casual relationships between risk aversion, price uncertainty, production decisions and investments in acquiring price information, it reveals a complex production decision behavior. In some cases, it is not *a priori* clear whether a change of a certain parameter, for example the cost of capital, leads to higher or lower production as this effect depends on a variety of further conditions. Considering the isolated effect of investments in acquiring price information (ignoring the adjustments on optimal inputs), we found that these investments are higher the higher the risk aversion, the lower the cost of information and the lower the discount rate. The impacts of improved information on farmers' production tends to be positive if the revenue risk through higher productivity is compensated by higher mean revenue and additionally reduced through investments into price information.

5.5.2. Empirical model

We apply an empirical model to test part of the above theoretical model with a primary household survey dataset. More specifically we empirically test if information improves the price signal, in other words, whether households with better access to information have more accurate price expectations. Our presumption is that a better price signal, as explained in the theoretical model, implies a more accurate price expectation. To this end, we identify relevant variables that affect the precision of smallholders in their expectation formation. Since we have data on smallholders' expectations of the harvest season prices at planting time, deviation of these expected prices *(p^e)* from realized harvest period output prices (p_{1+t}) can serve as a good proxy for the quality of the price signal. Suppose PE denotes this measure of the quality of the price signal, *henceforth* prediction error, and i and c are the household and crop indices as defined before, a simple model to explain PE can be specified as:

$$PE_i = \alpha + \gamma I_i + X'\beta + \omega_i \tag{5.18}$$

where PE is the deviation of each farmer's expected prices from realized market prices; I refers to ownership of information assets (radio, TV, or phone), which captures investment on information; *X* refers to a matrix of all explanatory variables that potentially affect the level of precision in price expectation of each farmer; ω_i is an error term; and α, γ, β are parameters to be estimated

Measuring prediction error (quality of the price signal)

We use four alternative but related measurements to proxy smallholder's prediction accuracy. Suppose t and $t+1$ refer to current sowing and next harvesting periods where the former is considered as the time of production decision and it is therefore the time when farmers form their price expectations for $t+1$; e denotes expectation; c, i, v denote crop, farmer and village specific prices respectively; and n is the number of crops that a farmer grows and reports his expectations for. The alternative measures of a farmer's price prediction error are defined as follows.

a) *Absolute Mean Price Error (AMPE)*

We measure *AMPE* as the ***absolute mean*** deviation of the farmer's price expectations from realized prices in the respective grain markets for n crops that the farmer grows

$$AMPE_i = {\sum_c^n \left(\left| p_{c,t+1} - p_{ic,t}^e \right| \right)} \big/ n$$

b) *Relative Mean Price Error (RMPE)*

This is similar to the above measure except that we take the ***relative mean*** deviation of farmer's price expectations from realized prices in the respective grain markets instead of the absolute deviation.

$$RMPE_i = \sum_{c=1}^{n} \frac{\left(\left|p_{c,t+1} - p_{ic,t}^{e}\right|\right)}{p_{c,t+1}} / n$$

The above two measurements assume that the farmer gives equal weight for each crop in his price expectations. However, a famer may invest more in acquiring better information for a crop that he produces for a market as compared for a crop that he produces for home consumption. This, in turn, affects his prediction accuracy of the respective crops. To account for this, we calculate deviations of weighted expected prices from realized prices, in other words, we use the market share of each crop to calculate price indices for each farmer and district. Using farmers' reported and expected prices for sowing and next harvesting periods, we obtain price indices for the respective seasons. Village level price indices are similarly calculated using observed prices in the respective nearby grain markets. Furthermore, we normalized both farmer and district specific harvest time price indices by the respective sowing time prices in order to account for inflation. Accounting for inflation is important to overcome endogeneity in the estimation that may arise due to heterogeneities in the farmers' understanding of the overall inflation on their price predictions. Thus, analogously with the above two measures of prediction accuracy or error, we calculate the absolute and relative index price prediction error for each smallholder farmer.

c) Absolute Index Price Error (AIPE)

We calculate *AIPE* as an ***absolute*** deviation of ***indices*** of farmers' expected prices from realized price ***indices*** in the respective markets/villages as

$$AIPE_i = \left|NPI_{v,t+1} - NPI_{i,t}^{e}\right|$$

where NPI refers to the inflation normalized price index.

d) Relative Index Price Error (RIPE)

RIPE is calculated as the ***relative*** deviation of ***indices*** of farmers' expected prices from realized price ***indices*** in the respective markets/villages as

$$RIPE_i = \frac{\left(\left|NPI_{v,t+1} - NPI_{i,t}^{e}\right|\right)}{NPI_{v,t+1}}$$

As measured by *RMPE*, for instance, the prediction error of smallholder farmers in our survey ranges from 0 (accurate prediction) to as far as 55% off, with a mean value of 18%. Similarly, the price prediction error ranges between 0 and 62% according to the *RIPE* measure, with a mean value of 17%. Figure 5.6 illustrates how we measure the PE using self-reported price data for the crops of interest in this study. The area in the dotted circle refers to realized (p_{t+1}) and expected (p^e) prices of the new harvest period; the latter are the expectations of smallholder farmers made at sowing time, t. The graph on the right panel is a replication of the corn example for better illustration. What we referred to as the prediction error is the vertical distance between the realized and expected price, indicated by the red arrow line.

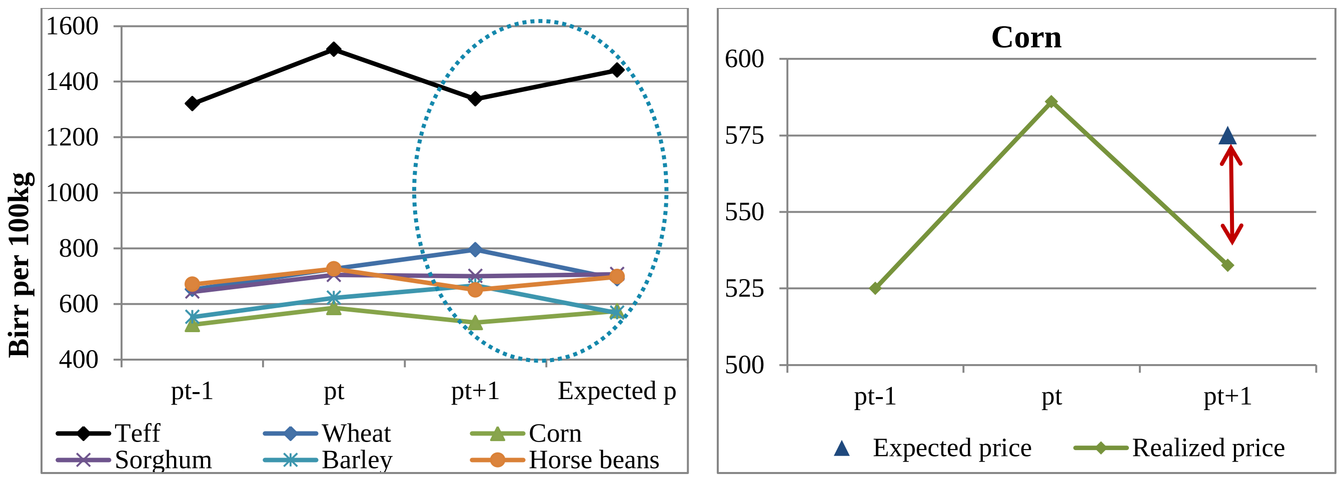


Figure 5.6. Illustration of prediction error using self-reported prices

Since these measures of smallholders' price prediction error combine the several crops that the farmer grows, there might be an "averaging-out" effect if a farmer who has large expectation error for one product tends to have small error for other products. In other words, these measures are not appropriate if the same farmer has large forecasting inconsistencies between products. In order to shed some light on this, we computed regressions and correlation coefficients from the magnitudes of the individual farmer's forecasting error for corn to that for sorghum and for wheat to that for barley.[41] The coefficients are presented in Table 5.8.

We find a significant degree of consistency in prediction errors between crops for the same farmer. Farmers who have the largest prediction errors for corn price tend to have the largest

[41] We chose these crop pairs since we have enough farmers producing both of these crops.

errors for sorghum too. This is also true for the expectation errors of farmers growing both wheat and barley. This hints that the mean-deviation would not cause the error for one crop to be offset by the error for another, suggesting also that crop-diversification would not lead to any better resource allocation by the farmer. Moreover, the crop-specific price forecasting (prediction) error, on average, ranges between 19% and 20% with comparable standard errors (see Table 5.5). This provides additional clue for the absence of any large systematic difference in the difficulty or ease of forecasting prices of one crop compared to the other.

Table 5.8. Consistency of farmers' prediction errors between crops

Crop-to-crop errors	Reg. coef.	Corr. coef.
Barley and wheat	0.49***	0.38***
	(0.10)	
Corn and sorghum	0.82***	0.47***
	(0.16)	

Notes: Standard errors are in parentheses. *** denote statistically significance at 1% level.

Furthermore, we transform the absolute measures of prediction error, *AMPE* and *AIPE*, using the inverse hyperbolic sine (IHS) method in order to interpret the regression coefficients as percentage changes, comparable with the relative measures.[42] We favor IHS over logarithmic transformation since some households in our sample have zero prediction errors, the log of which is not defined. The IHS is a logarithmic-like transformation that rather retains zero and negative values and has been applied by several studies (Bellemare et al., 2013; Burbidge et al., 1988; Moss & Shonkwiler, 1993).

5.5.3. Results and discussion

Table 5.9 presents the results of the expectation or prediction error of smallholder farmers in the study area. The four columns differ based on the measurements of prediction error, as discussed above. Although the results are mostly consistent across the different specifications, we prefer

[42] The IHS transformation of variable x can be given as: $ihs(x) = \ln\langle \theta x + (\theta^2 x^2 + 1)^{1/2} \rangle$ and the scale parameter θ is assumed to be unity in most applications.

the results from our preferred measure of prediction accuracy, the relative price index prediction error (*RIPE*)[43].

The estimated coefficients indicate that, controlling for access to markets and information and wealth indicator variables, households with female heads do better in price forecasts compared to male headed households. Moreover, as expected a priori, households with better experienced and educated heads have statistically and significantly smaller forecasting errors. The more smallholders depend on farm income as the major source of the family income, the more likely that they predict crop prices more accurately. This is expected as these households are more likely to invest more time and money in data processing and gathering since they have little alternative income sources. As expected a priori, smallholders who own information assets such as radio, television or mobile phones are more likely to make better price expectations compared to those who do not own any of these assets. Smallholders who follow price information through radio and television and more importantly those who communicate with friends or relatives who have better price information tend to forecast prices more accurately. This finding supports the implication of the theoretical model developed in the previous section. Another important factor is proximity of households to major local grain markets, which is also implied by the theoretical model that shows that costs of investing in acquiring information are higher for households far away from grain markets. This is consistent with the descriptive statistics as most households report that they usually visit nearby grain markets to get price information.

It is interesting that smallholders' forecasting error is closely linked with self-reported proxies of time preferences, i.e. the discount rate. The variable "discount rate" is measured from an elicited minimum amount of money that a household head would have to be given in six months in order to make him indifferent relative to a fixed amount to be given today. Regression results in Table 5.9 show that smallholders with higher discount rate, who are likely to be relatively poorer and more uncertain about the future, have larger forecasting errors. Such farmers underestimate the present value of future prices and they tend to get it wrong. This is in agreement with the theoretical model that shows that higher discount rates reduce investment into acquiring information.

[43] Besides controlling for farmers' heterogeneities regarding their understandings of inflation, this measure also weighs crop prices with their respective market shares.

Table 5.9. Factors that affect price prediction accuracy of smallholders

Dependent variable: Relative Mean/Index price Prediction Error				
Variables	**AMPE**	**AIPE**	**RMPE**	**RIPE**
Sex of head (1 if male)	0.1238**	0.1941***	0.0086***	0.0210***
	(0.055)	(0.062)	(0.003)	(0.004)
Age of head	0.0010	-0.0050**	-0.0002	-0.0006***
	(0.001)	(0.002)	(0.000)	(0.000)
Family size	-0.0064*	-0.0016	-0.0018	0.0001
	(0.004)	(0.012)	(0.001)	(0.001)
Head’s years of schooling	0.0024	-0.0238***	0.0008	-0.0013**
	(0.003)	(0.005)	(0.001)	(0.001)
Access to information	-0.0910***	-0.0731**	-0.0104**	-0.0205***
	(0.023)	(0.023)	(0.004)	(0.004)
Share of farm income	-0.3702***	-0.9684***	-0.0552**	-0.1252***
	(0.099)	(0.085)	(0.026)	(0.011)
Share of market surplus	-0.1486*		-0.0287**	
	(0.090)	–	(0.009)	–
Dist. to grain market (km)	-0.0141	0.0300***	-0.0004	0.0063***
	(0.009)	(0.008)	(0.001)	(0.001)
Dist. to extension agents’ (km)	0.0010	-0.0300	0.0002	-0.0042*
	(0.014)	(0.019)	(0.002)	(0.002)
Discount rate	0.0069***	0.0032***	0.0004**	0.0002**
	(0.001)	(0.001)	(0.000)	(0.000)
Constant	5.8893***	4.6186***	0.2694***	0.3228***
	(0.116)	(0.166)	(0.026)	(0.017)
District dummies	Yes	Yes	Yes	Yes
No. of crop dummy	Yes	NA	Yes	NA
Wald chi2 test (p-value)	0.00	0.00	0.00	0.00
Root MSE	0.91	0.91	0.01	0.11
Adjusted R-square	0.20	0.20	0.15	0.15
N	400			

Notes: Standard Errors are bootstrapped and clustered in seven *kebeles* (villages). ***, **,* denote statistically significance a 1%, 5% and 10% levels respectively. Note that since the dependent variable is either IHS transformed (APME & AIPE) or in ratio (RMPE & RIPE), the coefficients are economically relevant.

While we measure ‘access to information’ by ownership of any of the information assets – namely radio, television, or mobile – it may be necessary to investigate the differential impacts of each asset, if any. Table 5.10 presents the results using an exclusive ownership of mobile phones (column 2) and radio (column 3) as alternative measures of access to information.[44] Column (1) is the same as the last column in Table 5.9, and the dependent variable is *RIPE* in all cases. The results suggest that mobile phones alone play a statistically significant role in

[44] Since only less than 10% of our sample owns television (8%) or all three assets (7%), we only consider exclusive ownership of mobile or radio as alternative proxy for access to information.

improving the price forecasting accuracy of farmers. However, the marginal effect of an exclusive ownership of mobile phones is smaller than the effect of our preferred measure to information access. Smallholders may use the information assets as substitutes or as compliments depending on several factors. The results also highlight that ownership of a radio alone does not have a statistically significant effect on price prediction.

Table 5.10. Differential impacts of access to information on price prediction

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Sex of head (1 if male)	0.0210***	0.0198***	0.0209***	0.0188**
	(0.004)	(0.003)	(0.008)	(0.008)
Age of head	-0.0006***	-0.0006*	-0.0006***	-0.0021***
	(0.000)	(0.000)	(0.000)	(0.000)
Age x Access to info				0019***
				(0.000)
Family size	0.0001	-0.0004	-0.0005	-0.0002
	(0.001)	(0.001)	(0.002)	(0.002)
Head's years of schooling	-0.0013**	-0.0017*	-0.0016*	-0.0010
	(0.001)	(0.001)	(0.001)	(0.001)
Access to information[a]	-0.0205***	-0.0129**	-0.0061	-0.0893**
	(0.004)	(0.005)	(0.006)	(0.039)
Share of farm income	-0.1252***	-0.1221***	-0.1194***	-0.1221***
	(0.011)	(0.012)	(0.016)	(0.021)
Dist. to grain market (km)	0.0063***	0.0065***	0.0065***	0.0093***
	(0.001)	(0.001)	(0.001)	(0.003)
Dist. to market x Access to info.				-0.0038
				(0.003)
Dist. to extension agents' office (km)	-0.0042	-0.0038	-0.0042	-0.0046
	(0.002)	(0.003)	(0.003)	(0.003)
Discount rate	0.0002**	0.0002**	0.0002*	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.3228***	0.3061***	0.3022***	0.3755***
	(0.017)	(0.031)	(0.027)	(0.038)
District dummies	Yes	Yes	Yes	Yes
Wald chi2 test (p-value)	0.00	0.00	0.00	0.00
Root MSE	0.11	0.11	0.11	0.11
Adjusted R-square	0.15	0.12	0.11	0.15
N	400			

Notes: Standard Errors are bootstrapped and clustered in seven *kebeles* (villages). ***, **,* denote statistically significance a 1%, 5% and 10% levels respectively. [a]*Access to information* is measured as ownership of either a phone, radio or TV in (1 & 4), only a phone in (2), only a radio in (3).

The last column in Table 5.10 tests if the effects of some of the covariates (age and distance to market) are conditional on access to information. While older household heads have more experience and are more likely to have better price forecasts, the younger heads do better if they have access to information. This can be due to better knowledge of younger farmers with regard to using ICT tools and better understanding of the transmitted information. Another seemingly trivial but interesting finding is that proximity to grain markets is no more an advantage in terms of predicting prices as long as all households have access to information.

The Wald-tests at the bottom of Table 5.9 show that the proposed relationship between the prediction accuracy or prediction error and the set of control variables in the model is statistically reliable. Nevertheless, the variables we include in the regression do provide only part of the story on who predicts better. The regressors explain only about a fifth of the variation in prediction error among the smallholder farmers ($R^2 \approx 0.2$). One explanation for this is could be that output prices in Ethiopia have been very volatile in recent periods years (Rashid, 2011; Tadesse & Guttormsen, 2011). High price volatility reduces accuracy of producers' and consumers' forecasts of crop prices in the future (Binswanger & Rosenzweig, 1986). Given the stochasticity of output prices, the lucky farmer gets his expected price close to the actual value. Thus, the 'luck-factor' probably explains some of the remaining variation of smallholders' forecasting errors. There also appears to be a widespread exchange of price and other information among households, suggesting that the private information of a farmer who has the most timely and relevant information goes in to the public domain. This lowers the variation in the distribution of producers' forecasting error. Furthermore, farmers may tend to make certain psychological biases that may support the behavioral finance theory that smallholders are not fully rational in an economic sense (Kahneman & Riepe, 1998).

Implications for investing in market and information systems

It is important to assess whether it pays off for farmers to invest in acquiring information, and if so whether they are capable of doing that by themselves. The above estimated effect sizes on the relative prediction error of farmers provide a basis for analyzing the relevance of investing in acquiring more information by the farmers or in providing market information systems (MIS) by public or semi-public institutions. As explained in the theoretical model, acquiring information is costly for the farmers and they invest until a point where the marginal cost of acquiring information is equal to its additional benefit. Thus, they acquire *I** level of information although the marginal benefit of more information is still positive, as depicted by Figure 5.7. The marginal cost of acquiring information constitutes of among other things, purchasing information assets, travelling to nearby markets to inspect prices, and the opportunity cost of the time they spend searching for information. The marginal benefit, on the other hand, is more accurate (better quality) market and other information that potentially helps farmers form a better price expectation. As a result, farmers make a more informed production decision or they minimize loss.

Cost minimizing technological changes or public investments in information systems, which allow farmers to have access to better market information at lower cost, reduce the marginal cost of additional information and shift the marginal cost curve to the right.

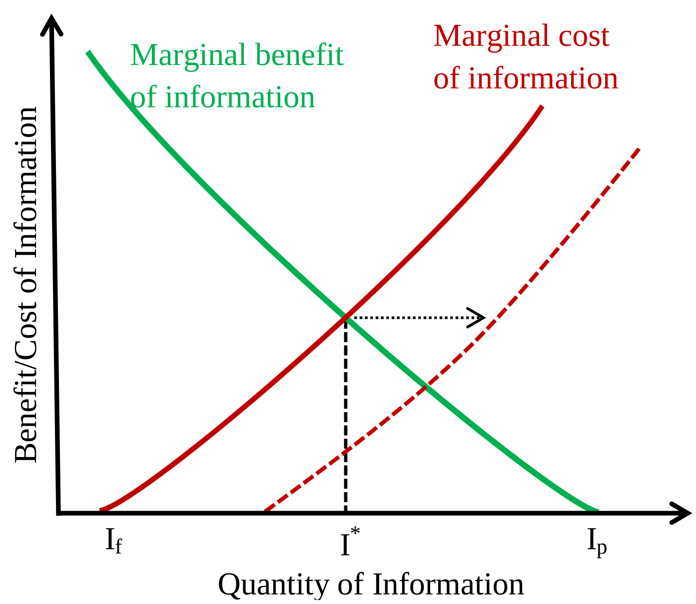


Figure 5.7. Optimal investment in acquiring information

As information is indivisible in its use and it is difficult to properly charge a market price, there is a positive externality while investing in acquiring information. As such, we argue that there is already a justification for the government to invest in MIS so that smallholder farmers have access to better quality information at a cheaper cost. Nevertheless, it is worthwhile to assess how much production loss by smallholders would be saved if the government invests in MIS or in physical infrastructure to reduce the 'effective' distance that households need to travel to nearby grain markets. To this end, we conduct a simulation analysis using our estimated coefficients in order to understand how much such an investment improves the production decision of farmers. We use the hypotheses, parameters, and quantities in Table 5.11 as a basis for our simulation.

Table 5.11. Parameters and quantities to simulate the benefit of investing in MIS

Base variables	**Value**	**Source**
Total grain production (Million MT)	25	CSA (2012/13)
Production elasticity (grains, weighted by production share)	0.20	Literature
Relative price prediction error (%)	20	Survey data
Grain price increase (%)	50	Hypothetical, but also observed data

<u>Hypothesis: A price increase of 50%:</u>

Assuming a competitive and well-functioning market, a 50% increase in output prices would lead to a 10% increase in production, which is about 2.5 million tons of grains. Nevertheless, farmers make forecasting errors (≈ 20%), and as a consequence they expect prices to increase by only 20% instead of 50%. In other words, they increase production only by 4% (by 1 million ton instead of by 2.5 million tons). We ask the following three questions in order to assess whether public investment in providing better and easily accessible market information pays off.

How much production loss would be saved by:

1) *Investing in providing information access to smallholder farmers?*
2) *Investing to halve the 'effective' distance smallholder farmers need to travel to close by markets?*
3) *Improving access to education so that the head of the household completes primary education (8^th^ grade)?*

Figure 5.8 illustrates how much of this production loss would have been saved under the above scenarios.

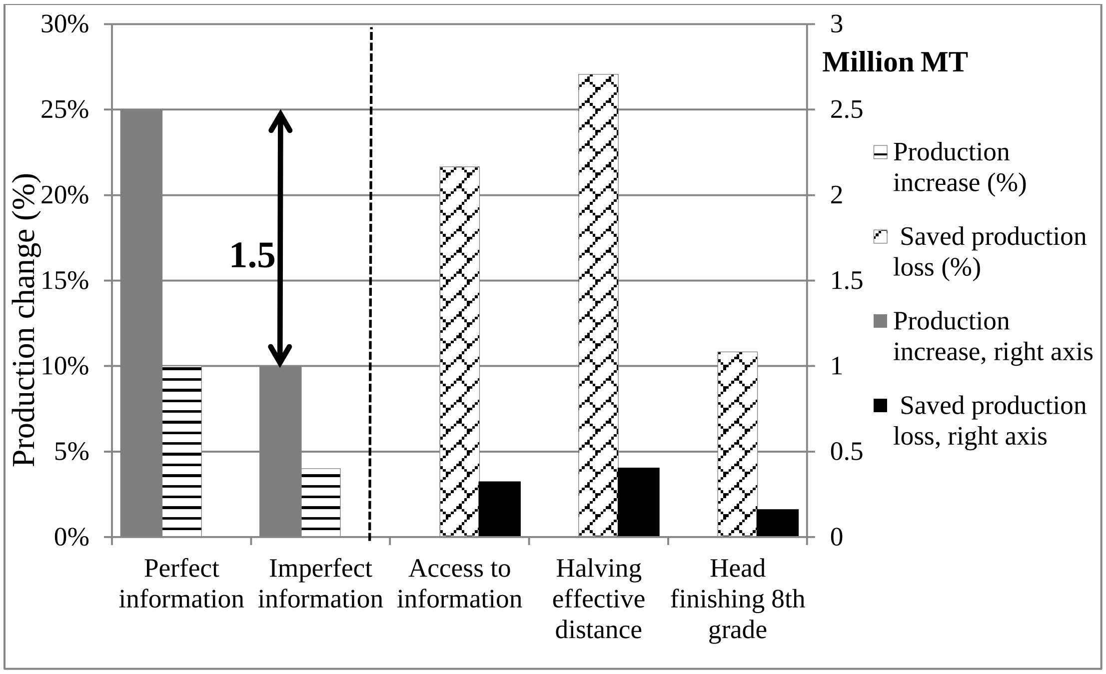


Figure 5.8. Benefits of investing in acquiring more information

One can see from Figure 5.8 that there will be 1.5 million metric tons of grains that would be lost with the status quo. However, public investments to provide farmers with price and market information and to halve the 'effective' distance they travel to nearby markets would save about 22% (0.32 Million MT) and 27% (0.41) of this production loss. Similarly, above 10% of the loss would be saved if household heads complete at least primary education. It is worthwhile to mention that the benefits of owning information assets – our measure for access to information – would be much larger if the content of information transmitted via ICTs is a better quality.

5.6. Conclusions

Given the intrinsic feature of agriculture that there is a time lag between production decisions and output realization, price expectations play a crucial role in the production, marketing and agricultural technology adoption of farmers. Producers involve themselves in gathering and processing price and other information, which they believe improves their price expectations. This process is costly for the individual farmer. Additionally, there is a certain level of externality in that the information a farmer obtains is a partially non-excludable public good that other farmers may use without paying. Accordingly, it might be necessary for the government to provide market information as public good through organized market information systems.

However, one should know the relevant information set that producers use in formulating their price expectations.

Using a primary survey dataset that elicits smallholders' price expectations for the next harvest period, this study assists to identify the relevant information set that farmers use in their expectation formulations. The empirical findings show that information regarding current and past output prices in nearby grain markets, central wholesale prices and seasonal rainfall shape smallholders' price expectations. There are some institutions that could potentially improve smallholders' access to market information in Ethiopia. The long-lasting Ethiopian Grain Trade Enterprise (EGTE) as well as the recently launched Ethiopian Commodity Exchange (ECX) and Agricultural Transformation Agency (ATA) aim at improving agricultural productivity and marketing efficiency in the country. These organizations may assist farmers in providing and disseminating accurate and timely central wholesale prices. In coordination with the National Meteorology Agency (MNA), these institutions might also provide better early warning information regarding seasonal weather conditions. Agricultural extension agents could also assist by disseminating timely and accurate output and input price information from nearby grain markets to farmers in villages.

Moreover, having data on farmers' expectations regarding the next harvest-period prices, which are realized at the time of writing this study, enables us to assess the factors behind smallholders' prediction accuracy. The empirical findings suggest that farmers who have better access to information and who reside closer to grain markets are more likely to have smaller forecasting error margins. This supports the above policy recommendation that improving information and physical infrastructure is important. In addition, farmers who have higher discount rates are more likely to have larger forecasting errors. This calls for assisting farmers in reducing future price and income uncertainties and enhancing their risk-management strategies.

It is not surprising that the control variables in our regression model explain only some of the variation in farmers' forecasting errors. First, Ethiopia is one of the countries where agricultural commodity prices have experienced significant variability in recent years (Rashid, 2011; Tadesse & Guttormsen, 2011). Large variability in output prices reduces the accuracy of smallholders in their price forecasting, resulting in suboptimal resource allocation and welfare loss. In situations of extreme price volatility, better performance in forecasting prices might be due to luck.

Therefore, agricultural policy makers should design proper price volatility management tools to improve smallholders' price expectations which, in turn, help farmers to make better production decisions. Furthermore, the variation of prediction efficiency among smallholders that is not explained by the relevant variables might suggest that cognitive or psychological bias might play a role (Rabin, 1998). The behavioral theory suggests that economic agents fail to be fully rational and make judgmental errors in maximizing their objective function (Ibid.). According to this theory, producers tend to, for instance, believe that prices will be in their interest, base their price forecast only on the recent past, and forget their mistakes (Brorsen & Anderson, 2001). However, further research is required to assess if such cognitive bias explains the remaining variation among smallholders in their price forecasting efficiency.

In summary, access to price and market information is crucial for smallholder farmers to make optimal production decisions. A simple simulation analysis shows that improving farmers' access to information and shortening the 'effective' distance that they need to travel to nearby grain markets would save a significant amount of production loss. Besides better physical and information infrastructure, proper price volatility management tools are required to improve smallholders' price expectations - thereby rural households allocate their production resources more optimally. Moreover, agricultural extension workers may have additional role in providing outlook information to assist farmers in developing more rational expectations about price risks.

A longer time period data would help to address questions such as whether smallholders who predict well for this year necessarily do so for other periods, which requires following up the same farmers to get a longitudinal information. Since producers usually revise their expectations from one production season to the next, this will enable us to understand whether smallholder farmers have historically become more or less accurate, and why. While we are able to show that better price prediction would save potential production loss following an increase in grain prices, further research is needed to test whether better price prediction essentially leads to optimal production decision and eventually to higher expected utility of profit. Moreover, it will be crucial to assess the cost of investing in market and information systems for the government.

6. General conclusions

The major objective of this thesis is to study how global food supply, and acreage in selected major producer countries, respond to international price levels and price volatility. As it is an integral part of any supply response study, the thesis further analyses price expectation formation and the role that information plays in the price prediction accuracy of smallholder farmers in the context of a developing country.

Uncertainty is a quintessential feature of agricultural commodity prices. Besides the traditional causes of price fluctuations, agricultural commodities are increasingly connected to energy and financial markets, with potentially destabilizing impacts on prices (Tadesse et al., 2014). In recent years, global crop production has faced a series of emerging issues and showed noticeable variations particularly in acreage. Factors such as ongoing developments in bio-technology, fluctuations in corn and soybean prices due to the growing demand for ethanol and changes in production costs affect producers' acreage allocation decisions, with a potential global food supply impact. Using global and cross-country data for the period 1961–2010, this thesis investigates the supply impacts of international price levels and volatility at a global level. Estimation of the supply response to input and output price levels and output price volatility is a necessary step in predicting the future global food supply effects of developments in output price levels and volatility. In addition to responding to price changes by reallocating acreage, producers react to expected price changes by making decisions that affect crop yield.

The findings reveal that, although higher output prices serve as an incentive to improve global crop supply as expected, output price volatility acts as a disincentive. Depending on the respective crop, the results show that own price supply elasticities range from about 0.05 to 0.35. Output price volatility, however, has negative correlations with crop supply, implying that farmers shift land, other inputs, and yield-improving investments to crops with less volatile prices. Comparison of the annual and the monthly acreage response elasticities from the time series acreage models suggests that acreage adjusts seasonally around the globe to new information and expectations. Given the seasonality of agriculture, time is of an essence for acreage response. The analysis indicates that acreage allocation is more sensitive to prices in the northern hemisphere spring than in winter and the response varies across months.

Furthermore, simulation analysis of the impact of the 2006–2010 price dynamics reveals differential effects on acreage, yield, and production of each crop. The overall acreage impact of the output and input price dynamics during this period is estimated to be, on average, positive for corn and soybeans, negligible for rice, and slightly negative for wheat. Furthermore, own-price volatility tends to dampen yield by about 1% to 2% for all the crops under consideration. Calculating the production impact from the acreage and yield simulations by the identity that production equals acreage times yield, we find that the net-impact on production is an increase of about 3% for corn, 2% for soybeans, 1% for rice, and a decrease of about 1% for wheat. One point to note here is that the adverse supply impact of price volatility is less pronounced for soybean and corn producers. The majority of the soybean and corn producers in the world are large commercial holders who are likely to be well informed about price developments. Thus, they are likely to be willing and able to absorb price risks.

With the help of the country specific results, we were able to identify two groups of countries: those with high price responsive markets and those with strong time trends. While prices drive most of the acreage change in countries characterized by the former market types, acreage expansion or shrinkage can be expected even if prices remain stable or slightly decreasing in the latter case. The acreage response models are able to adequately explain historical acreage fluctuations for most of these countries and crops except in a few cases. The forecasting tool might therefore be extended by further market analysis based on broader political and economic factors as well as short-term weather events that are not reflected in prices but that may potentially influence acreage decisions.

Finally, the results from chapter 5 show that information regarding current and past output prices in nearby grain markets, central wholesale prices and seasonal rainfall shape price expectations of smallholder farmers in Ethiopia. Furthermore, the results indicate that farmers who have better access to information and who reside closer to grain markets are more likely to have smaller price prediction errors. Using a simple simulation analysis, we show that improving farmers' access to information and shortening the 'effective' distance that they need to travel to nearby grain markets would save a significant amount of production loss. This calls for public and semi-public institutions to provide market information as public goods through organized market information systems in the country, and to improve the physical infrastructure. Nevertheless, further research is needed to test whether better price prediction essentially leads to optimal production decision and eventually to higher expected utility of profit. Moreover, it will be crucial to assess the cost of investing in market and information systems for the government.

In summary, the study explains why the recent high food prices have not brought about a large increase in global agricultural supply as one might have expected. The estimated short-run supply elasticities are generally small. Agricultural supply does not, in the short run, increase on a par with output price increases. In other words, agricultural producers need more time to make necessary production adjustments and investments to increase supply. Furthermore, this study identifies how much the increased latent output price uncertainty represented by price volatility weakens the global positive supply response towards price levels.

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Appendix I

Table A1. Seemingly unrelated regression results for the Annual acreage response model (Ch. 2)

Equation	Obs	Parms	RMSE	R-sq	Chi2	P
D_LWh_Area	48	11	0.02	0.41	34.72	0.00
D_LCorn_Area	48	11	0.02	0.52	55.82	0.00
D_LSoy_Area	48	11	0.03	0.55	65.56	0.00
LRic_Area	48	8	0.02	0.88	360.36	0.00

Variables	Coef.	Std. Err.	z	P>|z|
Wheat Area				
Lag wheat area	-0.25	0.13	-1.99	0.05
Wheat price	0.09	0.03	2.57	0.01
Corn Price	0.00	0.03	-0.14	0.89
Soy price	0.04	0.03	1.27	0.21
Rice price	-0.01	0.02	-0.58	0.56
Fertilizer price	-0.02	0.01	-1.53	0.13
Wheat vol	-0.90	0.34	-2.61	0.01
trend	0.00	0.00	-1.92	0.05
con	0.78	0.40	1.93	0.05
Corn Area				
Lagged corn area	-0.26	0.10	-2.57	0.01
Wheat price	-0.11	0.03	-3.57	0.00
Corn price	0.18	0.03	5.71	0.00
soy price	-0.02	0.03	-0.67	0.50
Rice price	0.00	0.01	0.01	1.00
Fertilizer price	0.02	0.01	1.36	0.17
corn price vol	-0.65	0.27	-2.39	0.02
year	0.00	0.00	0.26	0.79
_cons	-0.09	0.36	-0.23	0.82
Soybean Area				
Lagged soy area	-0.33	0.11	-2.89	0.00
Wheat price	0.02	0.05	0.40	0.69
Corn price	-0.19	0.06	-3.01	0.00
soy price	0.38	0.07	5.77	0.00
Rice price	-0.01	0.03	-0.20	0.84
Fertilizer price	-0.04	0.02	-2.11	0.04
Soy price vol	-1.52	0.47	-3.21	0.00

year	0.00	0.00	-0.51	0.61
_cons	0.37	0.64	0.57	0.57
Rice Area				
Lagged rice area	0.01	0.23	0.04	0.97
Wheat price	-0.03	0.04	-0.81	0.42
Corn price	0.02	0.04	0.38	0.71
soy price	0.00	0.04	0.10	0.92
Rice price	0.00	0.02	0.18	0.86
Fertilizer price	0.00	0.02	0.00	1.00
Rice price vol	-0.13	0.22	-0.61	0.54
year	0.00	0.00	18.31	0.00
_cons	2.55	0.51	5.02	0.00

Correlation matrix of residuals:

	D_LWh_Area	D_LMz_Area	D_LSoy_Area	LRic_Area
D_LWh_Area	1.00			
D_Lcorn_Area	0.11	1.00		
D_LSoy_Area	-0.23	-0.22	1.00	
LRic_Area	0.06	-0.17	0.16	1.00

Breusch-Pagan test of independence: chi2(6) =8.162, Pr= 0.23

Table A2. Annual global acreage response model with futures prices (Ch. 2)

		Newey-West		
Variables	Coef.	Std.Err.	t	P>|t|
	Wheat			
LWh_Area	-0.03	0.12	-0.24	0.81
LWh_futures price	-0.01	0.03	-0.58	0.57
Lcorn_futures price	0.07	0.04	2.07	0.05
LSoy_futures price	-0.05	0.03	-1.50	0.14
LFert_price	0.00	0.02	-0.16	0.88
Wh_vol	-0.25	0.45	-0.56	0.58
year	0.00	0.00	-1.18	0.25
_cons	0.67	0.57	1.18	0.25
	Corn			
Lcorn_Area	-0.34	0.14	-2.47	0.02
LWh_futures price	-0.04	0.03	-1.53	0.14
Lcorn_futures price	0.06	0.03	1.90	0.07
LSoy_futures price	0.02	0.02	1.02	0.32
LFert_price	0.01	0.02	0.33	0.75
Mz_vol	0.08	0.39	0.20	0.84
year	0.00	0.00	0.29	0.78
_cons	-0.10	0.40	-0.26	0.80
	Soybeans			
LSoy_Area	-0.08	0.25	-0.30	0.77
LWh_futures price	-0.05	0.05	-1.02	0.32
Lcorn_futures price	-0.12	0.09	-1.36	0.18
LSoy_futures price	0.10	0.08	1.26	0.22
LFert_price	0.04	0.04	0.91	0.37
Soy_vol	0.55	0.57	0.98	0.34
year	0.00	0.00	-0.12	0.91
_cons	0.11	0.69	0.16	0.87

Table A3. Monthly global acreage response model with futures prices (Ch. 2)

Variables	Coef.	Newey-West Std.Err	t	P>|t|
Wheat				
l12.LWh_Area	0.84	0.03	30.36	0.00
LWh_futures price	0.10	0.03	3.58	0.00
Lcorn_futures price	0.00	0.03	0.09	0.93
LSoy_futures price	-0.05	0.03	-1.93	0.05
LRic_spot price	-0.03	0.02	-1.58	0.11
LFert_price	0.00	0.02	0.11	0.92
Wh_vol	-1.16	0.45	-2.55	0.01
corn_vol	1.16	0.48	2.40	0.02
Soy_vol	0.78	0.35	2.18	0.03
Ric_vol	-0.24	0.27	-0.88	0.38
year	0.00	0.00	-0.25	0.80
MonthD1	-0.31	0.05	-5.71	0.00
MonthD2	-0.31	0.05	-5.71	0.00
MonthD3	-0.29	0.05	-5.61	0.00
MonthD4	-0.21	0.04	-5.54	0.00
MonthD5	-0.09	0.02	-5.27	0.00
MonthD6	-0.12	0.02	-5.54	0.00
MonthD7	-0.22	0.04	-5.72	0.00
MonthD8	-0.27	0.05	-5.76	0.00
MonthD9	-0.10	0.02	-5.83	0.00
MonthD10	0.08	0.02	5.37	0.00
MonthD12	-0.21	0.04	-5.67	0.00
_cons	1.90	1.30	1.46	0.14
Corn				
l12.Lcorn_Area	0.84	0.04	20.74	0.00
LWh_futures price	0.02	0.02	0.94	0.35
Lcorn_futures price	0.00	0.03	-0.16	0.87
LSoy_futures price	0.00	0.02	-0.24	0.81
LRic_spot price	-0.02	0.01	-1.69	0.09
LFert_price	0.01	0.01	0.64	0.53
Wh_vol	0.18	0.28	0.63	0.53
Mz_vol	0.32	0.33	0.98	0.33
Soy_vol	-0.14	0.36	-0.40	0.69
Ric_vol	0.03	0.28	0.13	0.90
year	0.00	0.00	1.09	0.28
MonthD1	-0.27	0.07	-3.75	0.00

MonthD2	-0.22	0.06	-3.65	0.00
MonthD3	-0.13	0.04	-3.32	0.00
MonthD4	0.11	0.03	3.88	0.00
MonthD5	0.16	0.04	4.02	0.00
MonthD6	-0.04	0.01	-2.71	0.01
MonthD7	-0.10	0.03	-3.36	0.00
MonthD8	-0.20	0.05	-3.67	0.00
MonthD9	-0.20	0.05	-3.84	0.00
MonthD10	-0.12	0.03	-3.89	0.00
MonthD12	-0.14	0.04	-3.84	0.00
_cons	-0.18	1.54	-0.11	0.91
Soybeans				
l12.LSoy_Area	0.96	0.01	87.69	0.00
LWh_futures price	0.01	0.04	0.23	0.82
Lcorn_futures price	0.09	0.04	2.58	0.01
LSoy_futures price	-0.10	0.05	-2.02	0.04
LRic_spot price	0.03	0.02	1.33	0.19
LFert_price	-0.02	0.02	-1.04	0.30
Wh_vol	0.32	0.57	0.56	0.58
corn_vol	-0.01	0.63	-0.02	0.98
Soy_vol	0.80	0.59	1.35	0.18
Ric_vol	-0.72	0.36	-2.02	0.04
year	0.00	0.00	1.85	0.07
MonthD1	0.01	0.03	0.24	0.81
MonthD2	-0.11	0.04	-2.50	0.01
MonthD3	-0.10	0.04	-2.43	0.02
MonthD5	0.06	0.01	4.18	0.00
MonthD6	0.06	0.01	4.44	0.00
MonthD7	0.00	0.03	0.05	0.96
MonthD8	-0.11	0.04	-2.64	0.01
MonthD9	-0.11	0.04	-2.67	0.01
MonthD10	0.02	0.02	0.68	0.50
MonthD11	0.10	0.02	5.06	0.00
MonthD12	0.05	0.02	2.93	0.00
_cons	-3.26	1.94	-1.68	0.09

Table A4. Short- and long-run own price elasticities of crop acreages (Ch. 2)

Model	***Crop***		***Short Run***	***Long Run***
Annual	Wheat		0.09	0.20
	Corn		0.18	0.23
	Soybeans		0.37	1.15
	Rice		0.02	0.06
Monthly	Wheat		0.07	0.43
	Corn		0.11	0.70
	Soybeans		0.14	3.59
	Rice		0.01	0.04
Month-specific	Wheat	*April*	0.13	0.26
		May	0.3	0.56
	Corn	*April*	0.11	0.17
		May	0.1	0.15
	Soybeans	*May*	0.18	0.87
		Jun	0.22	1.12
	Rice	*May*	0.02	0.06
		Jun	0.02	0.06

Notes: The long-run elasticities are the short-run elasticities divided by (1– α) where α is the estimate for the lagged dependent variable. This follows from the lag-structure of the auto-regressive model where $l_{t+s} = \alpha^s l_t + \beta \sum_{k=0}^{s-1} \alpha^k p_{t+s-k}$ (for brevity, other variables are omitted but could easily be considered in further additive terms). For large s, $\alpha^s l_t \to 0$ if $\alpha < 1$; and for a permanent price shift *p*, the geometric series converges to $l = \frac{\beta}{1-\alpha} p$, with $\frac{\beta}{1-\alpha}$ denoting the long-term elasticity. In the case of the annual model, we took the lagged coefficients from the regression of the data series before first differencing.

Table A5. Planting and harvesting seasons of wheat for selected countries

Country/Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Global shares for 2008 calendar year (%)	
													Acreage	Production
Argentina													2.10	1.24
Australia													6.02	3.07
Bangladesh													0.17	0.12
Brazil													1.06	0.88
Canada													4.53	4.24
China													10.51	16.10
Egypt													0.55	1.17
Ethiopia													0.63	0.37
EU27													11.64	21.96
India													12.34	11.56
Iran													2.34	1.17
Japan													0.09	0.13
Kazakhstan													5.78	1.90
Mexico													0.38	0.59
Myanmar													0.04	0.02
Nigeria													0.01	0.01
Pakistan													4.02	3.07
Paraguay													0.17	0.12
Russian Federation													11.57	9.37
South Africa													0.33	0.31
Turkey													3.60	2.63
Uruguay													0.21	0.20
Ukraine													3.17	3.81
United States													10.65	9.95
Uzbekistan													0.63	0.89
Others													7.45	5.10

Planting Harvesting Planting and Harvesting

Table A6. Planting and harvesting seasons of corn for selected countries

Country/Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Global shares for 2008 calendar year (%)	
													Acreage	Production
Argentina													2.11	2.66
Australia													0.04	0.05
Bangladesh													0.14	0.16
Brazil													8.90	7.14
Cambodia													0.10	0.07
Canada													0.73	1.33
China													18.02	20.56
Egypt													0.56	0.90
Ethiopia													1.07	0.46
EU27													5.34	7.62
India													4.93	2.42
Indonesia													2.42	1.94
Iran													0.15	0.22
Japan													0.05	0.00
Kazakhstan													0.06	0.05
Mexico													4.79	2.90
Myanmar													0.21	0.15
Nigeria													2.29	0.91
Pakistan													0.63	0.44
Paraguay													0.52	0.30
Philippines													1.61	0.83
Russian Federation													1.03	0.81
South Africa													1.99	1.57
Sri Lanka													0.02	0.01
Thailand													0.60	0.51
Turkey													0.36	0.52
Uruguay													0.05	0.04
Ukraine													1.52	1.33
United States													20.99	37.49
Uzbekistan													0.02	0.03
Viet Nam													0.87	0.56
Others													17.90	6.04

Table A7. Planting and harvesting seasons of soybeans for selected countries

Country/Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Global shares for 2008 calendar year (%)	
													Acreage	Production
Argentina													17.73	19.90
Australia													0.04	0.02
Brazil													20.90	25.95
Cambodia													0.07	0.05
Canada													1.18	1.43
China													11.92	6.92
Ethiopia													0.01	0.00
EU27													0.23	0.28
India													9.35	4.28
Indonesia													0.58	0.34
Iran													0.08	0.09
Japan													0.14	0.11
Kazakhstan													0.05	0.04
Mexico													0.09	0.07
Myanmar													0.16	0.09
Nigeria													0.60	0.26
Pakistan													0.00	0.00
Paraguay													2.42	2.72
Philippines													0.00	0.00
Russia													0.70	0.32
South Africa													0.16	0.12
Sri Lanka													0.00	0.00
Thailand													0.13	0.08
Turkey													0.01	0.01
Uruguay													0.57	0.33
Ukraine													0.55	0.35
United States													30.13	35.03
Viet Nam													0.19	0.12
Others													1.97	1.09

Planting Harvesting Planting and Harvesting

Table A8. Planting and harvesting seasons of rice (paddy) for selected countries

Country/Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Global shares for 2008 calendar year (%) Acreage	Production
Argentina			H	H	H	H			P	P	P	P	0.13	0.17
Australia			H	H	H					P	P	P	0.00	0.00
Bangladesh			P	P	P	P	PH	PH			H	H	7.05	6.82
Brazil	P	P	PH	PH	PH	H	H	H		P	P	P	1.79	1.74
Cambodia	H	H	H	H		P	P	P	P	P	P	PH	1.63	1.04
China		P	P	P	P	PH	PH	H	H	H	H		18.27	27.58
Egypt				P	P	P	P			H	H		0.47	1.06
Ethiopia	H			P	P	P					H	H	0.01	0.00
EU27		P	P	P				H	H	H	H		0.26	0.38
India	H		H	H	PH	P	P	P	H	H	PH	PH	28.46	21.77
Indonesia	P		H	H	H	H	P	P		PH	PH	PH	7.69	8.71
Iran					P	P		H	H				0.33	0.32
Japan				P	P				H	H	H		1.02	1.60
Kazakhstan					P	P			H	H			0.05	0.04
Mexico	H				P	P	P	P	P	H	H	H	0.03	0.03
Myanmar					P	P				H	H	H	5.06	4.79
Nigeria				P	P	P	P	H	H	H			1.50	0.61
Pakistan					P	P	P	P	H	H	H	H	1.85	1.45
Paraguay			H	H	H					P	P	P	0.02	0.02
Philippines			P	P	P	P	P	P	H	H	H	H	2.79	2.47
Russian Federation				P	P			H	H				0.10	0.11
South Africa				H	H	H			P	P	P	P	0.00	0.00
Sri Lanka	H	H	H	H					P	P	P	P	0.53	0.57
Thailand	PH	PH	P	H	PH	PH	P	P		H	H	H	7.08	4.64
Turkey				P	P	P			H	H			0.06	0.11
Uruguay			H	H	H					P	P	P	0.10	0.19
Ukraine				P	P				H	H			0.01	0.01
United States				P	P	P		H	H	H			0.76	1.34
Uzbekistan				P	P	P		H	H	H			0.04	0.02
Viet Nam	P	P	PH	PH	PH	PH	PH	PH	PH	PH	PH	PH	4.62	5.66
Others	PH	PH	PH	PH	PH	PH	PH	PH	PH	PH	PH	PH	8.28	6.74

Planting (P) Harvesting (H) Planting and Harvesting (PH)

Table A9. Country specific and common data sources

Countries	Area/production/yield data and sources
Argentina	Integrated Agricultural Information System (SIIA): http://www.siia.gov.ar/index.php/series-por-tema/agricultura Ministry of Agriculture, Livestock and Fisheries: http://www.minagri.gob.ar/site/agricultura/index.php
Australia	The Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES): http://www.daff.gov.au/abares/pages/data
Bangladesh	FAO, USDA
Brazil	Brazilian Institute of Geography and Statistics (IBGE): http://seriesestatisticas.ibge.gov.br/ National Food Supply Company (CONAB): http://www.conab.gov.br/ Ministry of Agriculture, Forestry and Fisheries (MAFF): http://www.elc.maff.gov.kh/
Cambodia	FAO, USDA
Canada	Canadian socio-economic information management system (CANSIM): http://www5.statcan.gc.ca/cansim
China	China Statistical Yearbook 2010
Egypt	FAO, USDA
Ethiopia	FAO, USDA
EU27	Eurostat: http://epp.eurostat.ec.europa.eu/
India	Directorate of Economics and Statistics, Department of Agriculture and Cooperation: http://eands.dacnet.nic.in/publications.htm
Indonesia	FAO, USDA
Iran	FAO, USDA
Japan	Ministry of Agriculture, Forestry and Fisheries : http://www.maff.go.jp/
Kazakhstan	FAO, USDA
Mexico	Secretariat of Agriculture, Livestock, Rural Development, Fisheries and Food: http://www.siap.gob.mx/
Myanmar	FAO, USDA
Nigeria	FAO, USDA
Pakistan	Pakistan Bureau of statistics: http://www.pbs.gov.pk/ http://www.finance.gov.pk/survey/chapter_12/02-Agriculture.pdf
Paraguay	FAO, USDA
Philippines	FAO, USDA
Russian Federation	FAO, USDA
South Africa	South African Grain Information Service (SAGIS):http://www.sagis.org.za/ http://www.daff.gov.za/docs/statsinfo/Abstract_2011.pdf FAO, USDA

Sri Lanka	Agriculture and Environment Statistics Division of the Department of Census and Statistics: http://www.statistics.gov.lk/agriculture FAO, USDA
Thailand	FAO, USDA
Turkey	Turkish Statistical Institute: http://www.turkstat.gov.tr/
Ukraine	FAO, USDA
Uruguay	Uruguayan Department of Livestock, Agriculture, and Fisheries: http://portal.gub.uy/
USA	Economic Research Service: http://www.ers.usda.gov/
Uzbekistan	FAO, USDA
Viet Nam	FAO, USDA
ROW	FAO, USDA
Other data and sources	
All countries, international spot prices	World Bank price database: http://go.worldbank.org/4ROCCIEQ50
All countries, futures spot prices	Bloomberg Database
Consumer Price Index (CPI)	Bureau of labor statistics: http://www.bls.gov/cpi/
Ethiopia, rainfall	National Metrology Agency (MNA)
All countries, Crop Calendar	FAO GIES , OCE USDA

Notes: Links are provided if applicable and available. All were accessed on/before August 15, 2014)

Appendix II

A) Perception of farmers about prices in the future: Survey questions

Please ask household heads regarding their prices expectations for selected crops (LEAVE EMPTY IF THE RESPONDENT DOES NOT KNOW)

Type of crop	9 How much do you think you will get for crops you produce and sell after the coming harvest in December next Ethiopian year?		10 Do you think it is possible that this price can be		11 Is/Are there grain market(s) in your *kebele*? 1 YES 2 NO, IF NO SKIP TO QUESTION 14	12 At what price could you sell the crop currently in your *kebele*?		13 For what price did you sell the crop after the last harvest in your *kebele*?		14 At what price could you sell the crop currently in the nearby grain market?		15 For what price did you sell the crop after the last harvest in the nearby grain market?		16 If I would pay you now to get some of your crops after the next harvest, what would be your minimum price? [*Start with a low price and increase the price step by step*]		17 What do you think will happen to prices in the next… *[1 increase, 2 decrease, 3 remain the same*]		
	Price in Birr	Unit **Code m**	twice as high as your prediction? 1YES 2 NO	half as low as your prediction? 1 YES 2 NO		Price in Birr	Unit **Code m**	Price in Birr	Unit **Code m**	Price in Birr	Unit **Code m**	Price in Birr	Unit **Code m**	Price in Birr	Unit **Code m**	6 months	1 year	2 years
Teff																		
Wheat																		
Maize																		
Sorghum																		
Barley																		
Horse beans																		

Code m: QUANTITY UNITS

1 KILOGRAMMES	11 BOBO	21 GAN	40 BIG MADABERIA	50 BUNCH (BANANAS)	60 EGIR
2 QUINTAL	12 PACKETS	22 ENSIRA	41 SMALL MADABERIA	51 MELEKIA/LIK	61 WESLA
3 CHINET	13 BAGS	23 GURZIGNE	42 DIRIB	52 GUCHIYE	62 MESFERIA
4 DAWLA	14 BUNDLES	24 TASSA	43 SAHIN/LOTERY	53 BEKOLE	63 KURFO
5 KUNNA	15 PIECES	25 KUBAYA/KELASA	44 MANKORKORIA	54 ENKIB	64 KOLELA
6 MEDEB	16 BARS	26 BIRCHIKO	45 PLATIC BAG/FESTAL	55 SHEKIM	
7 KURBETS	17 BOXES	27 SINI	46 ZURBA	56 NUMBER	95 OTHER (Specify)
8 SILICHA	18 LEAVES	28 GEMBO	47 AKARA	57 GOTERA	
9 AKMADA	19 LITRES	29 BOTTLES	48 SMALL PLASTIC BAG (MIKA)	58 LEMBA	
10 ESIR	20 KIL	30 BIRR	49 KERCHAT/KEMBA	59 SHIRIMERI	

B) Theoretical model: The role of information

We use the following substitutions to reduce complexity in the formal expressions:

Definition 1:

$\Gamma \coloneqq (1+r)(1-\alpha) + hRzq(2\alpha - 1)$

Definition 2:

$\Phi \coloneqq (1+r)(1-\alpha)(1+\beta) + hRzq(2\alpha - \beta - 1)$

Corollary 1:

The change of the optimal input *x* in *h* using (5.10a) and ignoring (5.10b)

$\frac{dx^*}{dh} = -\frac{zqRx^*}{(1+r)(1-\alpha)+hRzq(2\alpha-1)} = -\frac{zqRx^*}{\Gamma}$ from Equation (5.11) is negative if and only if $\Gamma > 0$.

Corollary 2:

$\Gamma > 0$ is equivalent to (1) $h < \tilde{h} \coloneqq \frac{1+r}{zqR}$ or (2) $h > \tilde{h}$ and $\alpha > \frac{1+r-hzqR}{1+r-2hzqR}$

Proposition 1 (Risk Aversion):

In the joint optimum, i.e. under (5.10a) and (5.10b),

$\frac{dx^*}{dR} = -\frac{hzqx}{\Phi}$ and $\frac{dI^*}{dR} = -\frac{I(hzqR+(r+1)(\alpha-1))}{R\Phi}$

Proof: Substituting $x^* = x^*(R)$ and $I^* = I^*(R)$ into (5.10a) and (5.10b) and taking the total derivatives of both equations in R and solving for $\frac{dx^*}{dR}$ and $\frac{dI^*}{dR}$ gives Proposition 1 (under the use of Definition 2).

Proposition 2 (Cost of Information):

In the joint optimum, i.e. under (5.10a) and (5.10b),

$$\frac{dx^*}{dk} = -\frac{2I^*(1+r)^2x^*}{zq\Phi} \quad \text{and} \quad \frac{dI^*}{dk} = -\frac{2(1+r)^2\Gamma I^{*2}}{(zq)^2 hR\beta\Phi}$$

Proof: Substituting $x^* = x^*(k)$ and $I^* = I^*(k)$ into (5.10a) and (5.10b) and taking the total derivatives of both equations in *k* and solving for $\frac{dx^*}{dk}$ and $\frac{dI^*}{dk}$ gives Proposition 2 (under the use of Definition 1 and 2).

Proposition 3 (Discount Rate):

In the joint optimum, i.e. under (5.10a) and (5.10b),

$$\frac{dx^*}{dr} = -\frac{((1+r)(1+\beta)-2hpqR)x}{(1+r)\Phi} \quad \text{and} \quad \frac{dI^*}{dr} = -\frac{2(1+r-hpqR)I}{(1+r)\Phi}$$

Proof: Substituting $x^* = x^*(r)$ and $I^* = I^*(r)$ into (5.10a) and (5.10b) and taking the total derivatives of both equations in *r* and solving for $\frac{dx^*}{dr}$ and $\frac{dI^*}{dr}$ gives Proposition 3 (under the use of Definition 2).