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The Role of Storage and Information in Stabilizing Food Prices and Supplies

Abstract

High and volatile food prices can push people into poverty, impact production and consumption, discourage investments, and lead to social unrest. Thus, due to occasional global food shortages as in 2007/08 and frequent regional shortages, many governments apply price stabilization policies. However, academic and political controversies about appropriate measures persist. This thesis explores the role of private and public storage, information, trade policies, international cooperation, and price-responsive production in stabilizing food prices.

In spite of its relevance for resource allocation, knowledge of the quality of global supply and demand estimates is limited. Hence, USDA, IGC, and FAO-AMIS estimates are compared using cointegration analysis, granger causality tests and three other methods. Estimation differences are found to be driven by methodological discrepancies rather than differing information. Differences are large for stocks and trade and persist over time revealing a comovement of the estimates. Averaging over sources can improve robustness and precision.

Despite its importance for the WTO and other trade agreements, knowledge of stabilization policies in an open economy is scarce. Additionally, private storage has been neglected in previous studies on international cooperation. Thus, emergency reserves, subsidized private storage, and strategic trade restrictions are compared in terms of their costs and impacts on price levels, volatility, and extreme events. A rational expectation partial equilibrium model is applied to capture dynamic interactions between agents. Private storage is found to be effective in reducing price volatility, whereas, complementarily, reserves are more effective in preventing extreme events. While free trade is usually beneficial, incentives for restricting exports may arise if stabilization policies are not aligned or the production variability differs too much. Asymmetric policies can explain large price increases as observed in 2007/08.

With some adjustments, the above model is used to present a new empirical validation method for the competitive storage model, the workhorse in numerical analysis of private storage. For the first time, the validation uses actual stock data. By applying a surface response methodology, this study derives a reduced-form equation which is shown to perform well as a surrogate model for private storage in theory and empirical tests. This allows directly quantifying stock determinants and facilitates high-dimensional modelling exercises.

As an empirical case study, India's public stockholding program, which suffers from surging stocks and costs, is analyzed. Necessary reforms require understanding how policies impact stocks, which is quantified for the first time. Thus, expected policy impacts on public rice stocks are deduced from economic theory and tested empirically. Private stock determinants are quantified by combining the reduced-form storage equation with an instrumental variable approach. Public storage is found to be inert, lacking crisis-responsive consumer protection and driven by the minimum support price, market supply, and export bans. The 29% increase of the real support price in 2008 contributed 4.9 million tons to public stocks, the export ban another 2.9. Each ton of public stocks crowds out half a ton of private stocks; however, speculative storage activities persist. Policy makers seem to be unaware of the problematic policy interactions.

China's demand growth and reluctance to rely on imports for its main food crops underline the need for a responsive supply, i.e. farmers making use of the latest price information. Hence, the time-dependent price responsiveness of supply is analyzed using the difference GMM estimator on province panel data. Production responds most to prices around planting time indicating the up-to-dateness of farmers' price information. High temperatures reduce production thereby highlighting the importance of limiting climate change and adapting to it.

Die Rolle von Lagerhaltung und Informationen bei der Stabilisierung von Angebot und Preisen von Nahrungsmitteln

Zusammenfassung

Hohe und volatile Nahrungsmittelpreise können Menschen in Armut drängen, Produktion, Konsum sowie Investitionen beeinflussen und Unruhen auslösen. Wegen gelegentlicher globaler Nahrungsmittelengpässe wie in 2007/08 und häufiger regionaler Engpässe verwenden viele Regierungen Preisstabilisierungspolitiken. Diese führen jedoch nach wie vor zu akademischen und politischen Kontroversen. Diese Arbeit erforscht die Rolle staatlicher und privater Lagerhaltung, von Informationen, Handelspolitiken, internationaler Kooperation, sowie einer auf Preisänderungen reagierenden Produktion bei der Preisstabilisierung.

Das Wissen über die Qualität globaler Angebots- und Nachfrageschätzungen ist trotz seiner Bedeutung für die Ressourcenallokation begrenzt. Daher werden Schätzungen des USDA, IGC, und FAO-AMIS mit Hilfe von Kointegrationstests, Granger-Kausalitätsstests und weiteren Methoden verglichen. Unterschiede zwischen Schätzungen bestehen über die Zeit fort, sind groß für Lager- und Handelsdaten und scheinen eher das Resultat verschiedener Methoden als abweichender Informationen zu sein. Eine Mittelung über die Quellen kann Präzision und Robustheit verbessern.

Trotz der Wichtigkeit für die WTO und andere Handelsabkommen ist das Wissen über Stabilisierungspolitiken in offenen Volkswirtschaften gering und frühere Studien zur Kooperation haben private Lager ignoriert. Daher wird die theoretische Kosteneffizienz der Stabilisierung durch Notfallreserven, subventionierter privater Lagerhaltung und strategischer Handelspolitiken verglichen. Ein partielles Gleichgewichtsmodel mit rationalen Erwartungen erfasst die dynamischen Interaktionen der Akteure. Private Lager sind effektiv in der Volatilitätsverringerung während, komplementär dazu, eine Notreserve effektiver in der Verhinderung extremer Preise ist. Freier Handel ist meistens vorteilhaft, aber Anreize für Exportrestriktionen entstehen bei asymmetrischen Stabilisierungspolitiken oder Produktionsvariabilitäten. Asymmetrische Politiken können auch starke Preisanstiege erklären, wie sie beispielsweise in 2007/08 beobachtet wurden.

Modifiziert ermöglicht das obige Model eine neue empirische Validierungsmethode für das kompetitive Lagerhaltungsmodel, das Standardmodel privater Lagerhaltung. Erstmals werden bei der Validierung Lagerbestände berücksichtigt. Mit Hilfe der Antwortflächenmethode wird eine reduzierte Gleichung hergeleitet, die ein genaues Ersatzmodel in der Theorie wie auch bei empirischen Tests darstellt. Dies erlaubt die direkte Quantifizierung von Lagerhaltungsdeterminanten und ermöglicht hoch-dimensionale Modellbildung mit privater Lagerhaltung.

Steigende Lagerbestände und Kosten von Indiens staatlichem Lagerhaltungsprogramm erfordern Reformen. Diese bedürfen Kenntnisse darüber, wie Regulierungen Lager beeinflussen, was erstmals in dieser Studie quantifiziert wird. Der Einfluss von Richtlinien auf Reisbestände wird aus ökonomischer Theorie hergeleitet und empirisch getestet. Determinanten privater Reisbestände werden mit der reduzierten Gleichung und einem Instrumentalvariablenansatz quantifiziert. Öffentliche Lager erscheinen träge, beeinflusst von Angebot, Exportverboten und *Minimum Support Price* (MSP) und entbehren eines krisenabhängigen Konsumentenschutzes. Der 29%ige Anstieg des realen MSP in 2008 führte zu 4,9, das Exportverbot zu 2,9 Millionen Tonnen mehr in öffentlichen Lagern. Jede öffentlich gelagerte Tonne verdrängt eine halbe private, aber spekulative Lagerhaltung besteht fort. Die problematischen Interaktionen von Maßnahmen scheinen unbekannt.

Chinas Nachfrageanstieg und Abneigung gegen Importabhängigkeit für Grundnahrungsmittel erfordern eine schnelle Reaktion der Produktion auf Preisänderungen. Daher wird die zeitabhängige Preisantwort der Produktion mithilfe des *difference GMM Schätzers* und Provinz-Paneldaten untersucht. Preise zur Anbauzeit stellen sich als am Wichtigsten heraus, was die Aktualität der Preisinformationen der Landwirte bezeugt. Hohe Temperaturen verringern die Produktion und unterstreichen so die Notwendigkeit den Klimawandel zu begrenzen und sich anzupassen.

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List of Abbreviations

Abbreviation	Long form / explanation
@	Indicates that something is measured at a certain time period
ADF	Augmented Dickey-Fuller
AMIS	Agricultural Market Information System (www.amis-outlook.com)
AR	Auto-Regressive
A-Temp	Average Temperature
CPI	Consumer Price Index
CSM	Competitive Storage Model
CV	Coefficient of Variation
ECOWAS	Economic Community of West African States
FAO	Food and Agricultural Organization of the United Nations
FCI	Food Cooperation of India
FE	Fixed Effects
FNS	Food and Nutrition Security
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
H-Temp	Highest Temperature
IFPRI	International Food Policy Research Institute
IGC	International Grains Council
IV	Instrument Variable
L.	Lagged (by one time period)
MOSPI	Ministry of Statistics and Programme Implementation
MSP	Minimum Support Price
NFSA	National Food Security Act
OLS	Ordinary Least Squares
OMSS	Open Market Sales Scheme
OWS	Other Welfare Schemes (besides the PDS)
PDS	Public Distribution System
RECS	Rational Expectations Complementarity Solver (Gouel 2013a)
RoW	Rest of the World
SD	Standard Deviation
USDA	United States Department of Agriculture
WPI	Wholesale Price Index
WSP	WholeSale Price
WFP	World Food Programme
WTO	World Trade Organization
X	Multiplied by (for interaction terms)

1 General Introduction

This introduction starts with a classification of the thesis within the framework of food and nutrition security (FNS). Then, it clarifies its motivation by posing the question of whether government interventions are useful and evaluating the current risk of food scarcities. Subsequently, the debate on information availability and usage, trade restrictions, and public stockholding is summarized while open issues are highlighted. Subsequently, objectives and research questions are formulated and put into perspective regarding the state of the debate. Finally, an outline of the thesis is provided.

1.1 Motivation

1.1.1 Classification of this thesis within the FNS framework

The Millennium Development Goals, now followed by the Sustainable Development Goals, have increased global attention in achieving food security for all. Despite substantial progress, there are doubts whether ending hunger and poverty can be achieved by 2030 as foreseen in the Sustainable Development Goals (United Nations 2015a). Food security consists of food availability, accessibility, utilization, and the stability of these three dimensions (FAO 1996). The stability of food availability, the only category considered in this thesis, contains a short-run and a long-run component. The latter, which can be seen from a Malthusian perspective (Malthus 1798), asks whether the production trend can keep up with the demand trend. Demand is driven by the rising population (United Nations 2015b), the increasingly resource-intensive diets (e.g. Alexandratos and Bruinsma 2012; Daniel et al. 2011; Mekonnen and Hoekstra 2011, 2010), persistently high food losses (e.g. Gustavsson et al. 2011; Parfitt et al. 2010), and the increasing biofuel use (e.g. Abbott et al. 2011; Coyle 2007; Haberl et al. 2011).

Short-term supply shortages are caused by unexpected supply shocks implying that supply levels are below the trend. Potential causes are manifold. First, natural disasters or extreme weather events may lead to harvest shortfalls. Second, underlying market conditions may provide bad incentives for private market actors such as prices fixed by the government resulting in inefficient resource allocation decisions. Financial market conditions which boost coupling of non-food with food commodities (compare e.g. Basak and Pavlova 2013; Tang and Xiong 2012) or let “animal spirits” and mass psychology drive asset prices (e.g. Shiller 2003) serve as further example. Third, unexpected policy changes may lead to sudden demand or supply changes. For example, export bans may lead to a domestic surplus but shortages abroad. Climate change may have long-term impacts, e.g. through higher temperatures. Besides, it may amplify short-term supply fluctuations, e.g. by increasing weather variability.

Even if food is abandoned and accessible, it does not necessarily imply that it is sufficient to meet nutritional needs, i.e. to prevent “hidden hunger”. However, this thesis focusses on the calorie availability to avoid food shortages which lead to undernutrition. Four main sub-pillars constitute the components of food availability: production, storage, transportation, and processing. Storage can be divided into public storage, private speculative storage, which is profit-maximizing, and private non-speculative storage. The latter might contain motives such as preventing interruptions of production processes or material flows (Carter and Giha 2007; Williams 1987). This thesis focusses on public and private speculative storage as parts of the storage category, supply response as a part of the production category, and international trade as part of the transport category. It investigates how storage and trade behave in different situations, both theoretically and empirically, and illustrates how price information is used for the supply response in China. Given the importance of high quality and up-to-date information, the analysis starts with assessing the quality of available supply and demand estimates.

1.1.2 High food prices and volatility: should governments intervene?

High and volatile food prices can have serious consequences. Poor net consumers, including many small farmers, may suffer under high prices which may lead to insufficient food intake and a reduction of investments into education, health, and other areas. In contrast, net producers may benefit from high prices. While there is mostly consensus that high prices have negative consequences in the short run (Arezki and Brückner 2011; Ivanic and Martin 2008), the long-term impacts are not clear and are often debated (e.g. Headey 2014 find that high food prices are pro-poor in the long run; compare also Minot and Dewina 2015; Swinnen 2010). This question typically depends on the share of net producers and net consumers that are regarded as poor and on the responsiveness of rural non-farming wages to food prices.

In contrast, very volatile food prices can be a challenge for both consumers and producers because the introduced risk affects the decision making process of risk-averse agents (e.g. Moschini and Hennessy 2001; Sandmo 1971). Net producers in developing countries may lower their input use and production under risk (Binswanger and Rosenzweig 1986; Carraro and Romano 2015; Haile et al. 2014) while net buyers may consume less under risk than under certainty (Banerjee and Duflo 2007). Therefore, potential negative welfare impacts of excessive food price volatility are widely acknowledged although there is less consensus about the actual losses (Myers 2006). Nevertheless, food price shocks can have direct negative nutritional impacts (compare e.g. Ecker and Qaim 2011; Kalkuhl et al. 2013).

The inability to ensure a sufficient food intake may have severe long-term consequences (Chen and Zhou 2007; de Janvry et al. 2006). Many mechanisms are used to cope with the income and consumption risks, such as diversification of cropping patterns, usage of risk-reducing inputs, off-farm employment, storage or acquisition of other assets (Rosenzweig and Stark 1989; Rosenzweig and Wolpin 1993; Townsend 1994). Despite being valuable, these coping mechanisms do not seem to fully compensate for the lack of formal insurance markets (Foster 1995; Townsend 1995). This underlines the need for governments to intervene.

Until the food crisis in 2007/08, a widespread view was that only market-based approaches should be used to stabilize prices and prevent negative impacts on the poor. Meanwhile, governments were supposed to intervene only in an acute crisis only with targeted and short-lived measures (e.g. World Bank 2005). However, this "dominant doctrine" (Galtier 2013) or "best practices" (Abbott 2010; Timmer 2010) has been criticized for underestimating important factors. These include the degree of price instability, the magnitude of exposure by producers and consumers, the influence of price instability on overall welfare (Abbott 2010; Galtier 2013), and potential social unrest (Arezki and Brückner 2011). Accounting for these factors often provides a rationale for governments to intervene. Additionally, markets in developing countries are typically highly incomplete and it has long been known that for incomplete markets, government interventions such as public stocks can increase overall welfare (Innes 1990; Newbery and Stiglitz 1981). Therefore, calls have increased to (re-) explore other types of stabilization mechanisms with a particular focus on public stocks and reserves (see section 1.1.6).

Policies to either prevent food price spikes and excessive volatility, i.e. stabilization measures, or to find measures to minimize their impacts on the poor, i.e. compensation measures, are used in many developing countries. Stabilization measures comprise holding public stocks, restricting exports or reducing import restrictions, and subsidizing production. Compensation measures include maintaining social safety nets or distributing subsidized grains. It has been argued that only the prevention of food crises rather than support in the form of coping strategies is able to fully impede welfare losses for poor households (Timmer 2010). Corresponding stabilization policies constitute the focus of this thesis. Before discussing them, the extent to which the world and individual countries are still at risk will be illustrated.

1.1.3 Food prices and excessive volatility in the 21st century: are we still at risk?

From the 1980s onward, food prices were relatively stable until they increased mildly in 2004, surged in 2007, and reached a nominal all-time high in 2008. After a short period of declining prices, they increased again in 2010 and 2011. Afterward prices declined again but the confidence in international markets and the willingness to exclusively rely on market-based stabilization approaches, in particular free trade, has faded.

Studies have identified the following drivers of the food crisis in 2007-2008: increased biofuel demand, harvest failures, high energy prices, depreciation of the U.S. Dollar, trade restrictions, global economic growth, low stock-to-use levels, and increased financial trading of food commodities, e.g. with index funds (Collins 2008; Gerber et al. 2008; Headey and Fan 2008; Headey 2010; Tadesse et al. 2014). In recent years, food prices decreased and became more stable again. At the same time, stock-to-use ratios have increased and energy prices as well as input prices remain low. Therefore, chances of entering a new global crisis are currently low. However, agricultural markets have not seen any new global measures which could provide more resilience against shocks. While the biofuel demand could be better regulated in the future, the other driving forces behind the last crisis still persist and additional protection measures are largely missing. An exception is the implementation of the Agricultural Market Information System, a G20 initiative which aims at improving data and offering a platform for rapid exchange between senior policy makers to align policy measures (AMIS 2011a). However, the influence of this initiative during a crisis still needs to be proved. Shocks to agricultural production may even become more frequent and severe than in the past. Climate change drives global temperatures up, often resulting in reduced yields, and increases weather variability thereby introducing higher risks (IPCC 2007; Tao et al. 2006). Hence, the current situation of relatively calm global food markets should be used to find measures which provide more resilience against future shocks, in particular harvest failures.

Individual regions may face very different situations than those of global markets. Local production shortfalls may have severe impacts even if global supply is abundant. Countries may be particularly vulnerable if (1) supplies fall short or demand increases in a sudden and unexpected manner such that trade and production cannot adjust quickly enough; (2) net exporters become net importers due to the supply shortage which may lead to price increases as high as twice the trade costs to global markets; (3) a production shortfall is accompanied by a depreciation of the local currency against the U.S. Dollar such that imports become more expensive; (4) the affected region is very remote such that trade is costly and time-consuming.

Currently, for example, some countries face severe food shortages which are mostly caused by the ongoing El Niño. Supply shortages in Ethiopia have made 4.5 million people dependent on food aid due to poor rainfall (Government of Ethiopia 2015). In Malawi, 2.5 million people face acute food insecurity due to flooding followed by a drought which has led to massive production shortfalls (FEWS NET 2015a). Assistance was planned but is deferred indefinitely due to a lack of funds. In Zimbabwe, poor rainfall reduced production substantially resulting in up to 1.5 million people suffering under food insecurity (FEWS NET 2015b). In the Americas, El Salvador, Honduras, Guatemala, Colombia, Ecuador, Paraguay, and Peru have declared states of emergency in affected provinces (Oxfam 2015).

As the risk of global supply shortages persists and regional shortages are frequent, policies should now focus on implementing measures to increase market resilience and prevent short-sighted policy responses in the future. Such measures are discussed in the following sections.

1.1.4 High-quality and up-to-date information: important for market resilience?

If prices reflect all information that is available, markets are considered to be efficient (Fama 1970). However, this has no implications about the quality and timeliness of the available information set. Yet, if information is of low quality or outdated, uncertainty and risk may increase. Risk implies that the probability distribution of potential outcomes is measurable whereas uncertainty implies that no statements about the probability distribution of outcomes can be made. Risk and uncertainty about supply and demand conditions may result in price volatility, i.e. the dispersion of a price series from its trend, or, if information sets quickly change, price spikes, i.e. sudden and large short-term price changes. In contrast, expected price changes such as seasonal price variations for seasonal crops are not associated with risk or uncertainty. Decision making processes by private market actors as well as governments are affected by risk and uncertainty. For example, producers may lower their input use and production (Binswanger and Rosenzweig 1986; Carraro and Romano 2015; Haile et al. 2014), net buyers may consume less (Banerjee and Duflo 2007), governments may focus more on self-sufficiency irrespective of their comparative advantages (compare e.g. von Braun and Tadesse 2012), and firms as well as farms may reduce investments (Dawe and Timmer 2012; Timmer 1989). Furthermore, poor people may fall into poverty-traps (Dawe and Timmer 2012). Beyond the agricultural sector, the whole economy may be affected (Ramey and Ramey 1995). Thus, governments should invest in reducing risk and uncertainty. The most market-oriented way to achieve this is by collecting and disseminating high quality and up-to-date information (for other options see e.g. Kornher and Kalkuhl 2013). This incentivizes investments and allows market actors to make better resource allocation decisions. Producers and traders can then react quickly to anticipated scarcities and thereby prevent a potential domestic crisis, given enough time to respond and sufficient global supplies. Private stocks also increase if risk is reduced (Gouel 2013b; Koester 1986; compare also chapter 3). Overall, availability of high-quality information therefore improves the resilience of markets.

Realizing the need to improve information on agricultural supply and demand conditions, the Agricultural Market Information System (AMIS) was set up by the G20 countries in 2011 to improve data and align policy responses in times of crises (FAO et al. 2011; G20 2011a). Progress has been made in collecting and harmonizing data (AMIS 2012a). However, the degree of uncertainty in the data provided by AMIS remains unclear.

This thesis addresses two issues in this area. Chapter 2 presents a comparison of grain supply and demand estimates from the USDA, FAO-AMIS, and IGC. Results illustrate which estimates suffer from higher levels of uncertainty, how similar the information available to the sources is, and how estimates evolve over time. Chapter 6 analyzes how up-to-date price information of Chinese farmers is on the macro-level. This indicates how resilient the Chinese agricultural markets are, in particular, up to which point the supply can respond to changed market conditions and thereby help to prevent a crisis.

1.1.5 Trade restrictions: effective intervention or collective action problem?

Policies to stabilize food prices and supplies aim at influencing trade, storage, production, or demand. Typically, trade and storage are considered as the most important means of price stabilization. Especially during times of crisis, governments tend to intervene into markets by controlling trade or storage. During the world food crisis in 2007/08, at least 35 countries sold grains from public stocks, at least 25 banned or restricted exports and at least 43 countries reduced tariffs and custom fees (Demeke et al. 2009). Many important surplus countries, particularly for rice, were among those which restricted exports in order to prevent domestic price increases. These included Argentina, Cambodia, Egypt, India, Kazakhstan, Russia, Ukraine, and Vietnam (Headey 2010). Domestically, these measures have often been very effective (Anderson et al. 2013) as they prevent the otherwise often substantial transmission of global prices to domestic markets (e.g. Kalkuhl 2014). In India, for example, the rice price increased by only 7.9%, whereas the world rice price increased by 160% between June 2007 and June 2008 (World Bank 2010). In a theoretical study, it has even been shown that similar restrictive trade policies are part of an optimal strategy to stabilize prices for a small open economy (Gouel and Jean 2015). However, these beggar-thy-neighbor policies come at the cost of the other countries on the world market because export restrictions, imposed by a surplus country, will lead to a further increase in global prices (Anderson et al. 2013). In 2007/08, these restrictions played an important role in setting the world price for corn, wheat, rice and soybeans (Anderson et al. 2013; Headey 2010). Similarly, price volatility of domestic prices is not reduced but only redistributed between countries while global volatility is increased (Martin and Anderson 2011). If importers lower import restrictions while exports increase export restrictions, this can create the illusion of successful policies when domestic prices are compared to world prices (Gouel 2014a; Martin and Anderson 2011).

Furthermore, while consumers in surplus countries typically benefit from export restrictions, producers and traders do not. Such restrictive trade policies have been reported to distort markets, especially producer’s incentives inside and outside of the countries which use these policies (Anderson et al. 2010). Countries which impose export taxes or bans reduce the expected profits for producers thereby decreasing production. This prevents an appropriate supply response to the globally experienced scarcity. Countries withstanding the use of such measures experience an increase in volatility (Martin and Anderson 2011) which may again result in lower levels of production (Haile et al. 2013). Overall, this causes suboptimal levels of production, i.e. the supply does not respond to the actual scarcity, resulting in even higher prices on the world market. Therefore, the need to improve international grain markets, in particular by reducing trade restrictions, has often been emphasized (e.g. Bouët and Laborde Debucquet 2012; von Braun 2008). However, different countries face very different incentives. Even though it might be desirable to limit export and import restrictions from a world-wide perspective, exporting countries focusing on local price stability may continue to use them as long as they are not bound by an international agreement. To such an agreement they are unlikely to commit unless facing clear incentives. As a result, this situation represents a classical collective action problem: If countries act individualistically rational[1] and in an

[1] i.e. maximize their own expected return

uncoordinated manner, the outcome for everyone involved will be worse than if all countries cooperate and choose a common strategy (Bouët and Laborde Debucquet 2012).

The WTO membership imposes limits on the extent to which imports can be restricted. However, bindings are higher than historically applied rates and therefore effectively have a very limited impact (Martin and Anderson 2011). The other half of the beggar-thy-neighbor problem is fully unregulated as the WTO does not impose any limits on export restrictions. Addressing these issues is crucial but complicated. No mechanism is known to incentivize free trade for all in times of crisis. While the agricultural sector only accounts for 6% of world trade, it also represents 70% of potential real income gains from reformed trade (Laborde and Martin 2012). Hence, neglecting agriculture would substantially curb potential benefits. Between countries with similar interests and preferences, a commitment to regional cooperation by providing appropriate incentives is much easier to achieve, and accordingly many regional trade agreements have been formed. However, these detract from global integration and provide only an economically less efficient second-best solution (Koester 1986).

This thesis contributes to the ongoing discussions about trade policies in several ways. The uncertainty of trade estimates are emphasized in chapter 2. Chapter 3 addresses the lack of knowledge about storage policies in an open economy (Gouel 2014a). It is investigated how trade restrictions can prevent the leakage of benefits of domestic price stabilization policies into global markets. Furthermore, the collective action problem is analyzed by revealing under which circumstances countries face incentives to cooperate and leave trade unrestricted and under which circumstances they face incentives to impose restrictions. Alternative options to solve the collective action problem are discussed in section 3.6. Chapter 4 focusses on private storage but also illustrates how trade affects private storage. Chapter 5 presents the impacts of India’s trade restrictions on domestic public and private stocks. Yet, the main focus of this thesis lies on storage policies as discussed in the subsequent paragraph.

1.1.6 Public storage: inefficient and market-distorting or a complement to private stockholding?

Traditionally, market interventions by holding public stocks were performed in the way of so called buffer stock programs which protect producers by buying grains when prices are low and protect consumers by selling their stocks when prices are high. Meanwhile, buffer stock policies have been heavily criticized for various reasons. First, they are consistently reported to be less efficient than other measures to stabilize prices, be they trade oriented (Bigman and Reutlinger 1979; Gouel 2014a; Srinivasan and Jha 2001, 1999) or private storage oriented (Glauber et al. 1989; World Bank 2005). Second, buffer stocks have been reported to only benefit producers at the cost of consumers (Helmberger and Weaver 1977). Third, buffer stocks may distort markets and significantly impact the behavior of private market actors such as stockholders, traders, and producers (Glauber et al. 1989; World Bank 2005; Zant 1997).

Fourth, updating the stabilization range may be a source of controversy (Gilbert 2011a). Finally, buffer stock programs are usually prone to speculative attack (Salant 1983). The removal of the US public stock scheme in 1996 was found to have left the level of price stability unchanged because private stockholding increased (Lence and Hayes 2002).

Overall, these reasons have led to a widespread aversion against buffer stocks among academics and policy analysts. Other types of market interventions have received similar critique. So called “best practice” strategies (labbeling e.g. by Abbott 2010; Timmer 2010) relying on market based approaches without government interventions combined with social safety nets have instead been advocated by the World Bank (2005) and others. However, during and after the world food crisis in 2007-08, this view has been reassessed. Different important factors have been underestimated in the analyses which yielded the above results and therefore a reevaluation is necessary. The most important underestimated factors include the degree of market incompleteness in many developing countries, the degree of global and domestic price instability, the magnitude of exposure by producers and consumers, and the influence of price instability on the overall welfare (Abbott 2010; Galtier 2013). Besides, market conditions have changed, storage technology has improved, and the inherent transparency of public storage compared to private stocks has been acknowledged (HLPE 2011). This underlined that previous results may not hold any more. As a result, calls have increased to (re-)explore various types of stabilization mechanisms with a particular focus on public stocks and reserves (Abbott 2010; Galtier 2013; von Braun and Torero 2009). Different operational structures of public stocks have been proposed including buffer stocks (HLPE 2011; Oxfam 2011), emergency reserves (Abbott 2010; von Braun et al. 2014), virtual reserves (von Braun and Torero 2009), and regional (international) reserves (ECOWAS Commission 2012; HLPE 2011; von Braun and Torero 2009) with some of them overlapping.

Reserves, in contrast to buffer stocks, focus on protecting consumers from extreme prices but they do not impose lower limits on prices. As a result, much of the criticism of buffer stocks does not apply. In particular, their costs are well defined and adjustable by the setup such that no cost surges arise. Second, they can be better combined with free trade thereby providing two simultaneous stabilization measures. This is possible because reserves are rarely used and therefore incentives to restrict trade are rare; however, they do occur (compare chapter 3). Third, depending on the design, reserves can be much less market-distorting as will be demonstrated in chapter 3. Hence, private storage can be kept as another stabilization mechanism apart from the reserve. Fourth, the controversy about setting the intervention triggers is reduced; yet, it still persists even if there is only one trigger to adjust. Compared to a buffer stock, a reserve is also less prone to mismanagement as operational rules are simpler and easier to observe. This gives hope that in contrast to buffer stocks which often increased during the food crisis in 2007/08 (compare chapter 5 and Anderson et al. 2013), partly due to increased lower price bounds, reserves would actually be depleted in order to stabilize prices.

If shared between countries, such a reserve may work as an insurance mechanism: All countries contribute in times of ample supplies while individual countries may take grains from the reserve in times of need, e.g. if domestic supplies fall short (compare e.g. Kornher and Kalkuhl 2015; Romero-Aguilar and Miranda 2015). This risk sharing mechanism works best if supply shortages are unlikely to coincide in the participating countries. But even if they do, such a reserve will still help to dampen the effects and allow more time to arrange for other measures such as trade to compensate the shortage.

Profit-maximizing private storage is a stabilization mechanism which is efficient in reducing price volatility without producing any fiscal costs for the government (compare chapter 3 and Gouel 2013c). Thus, public storage schemes as well as trade policies should be set up in a way that does not crowd out private storage.

This thesis provides important contributions to several of the issues discussed above. Chapter 2 reveals the bad quality of data on stocks. Chapter 3 compares the fiscal costs and price stabilization efficiency of a public reserve with subsidized private storage. Market distortions, i.e. impacts on other market actors, are quantified and some guidance is given for the conditions under which reserve-trade cooperation between countries can be achieved. Chapter 4 provides empirical evidence for the validity of the competitive storage model, the workhorse for modelling speculative private storage. A surrogate model is presented which can be used for high dimensional modelling exercises and for the direct empirical quantification of stock determinants. This is used in chapter 5 to quantify drivers and interactions of public and private rice stocks in India.

1.2 Objectives and research questions

This thesis addresses several of the open issues discussed in the previous sections. Here, the objectives and research questions are subsequently summarized.

The importance of information of high quality has been underlined in the previous sections. However, knowledge about the quality of global supply and demand estimates is limited. Different sources provide different estimates giving rise to the research question in **chapter 2**:

1. How and why do the supply and demand estimates from different sources differ?

Five different methods are used to analyze differences in the estimations. The hypothesis that information about supply and demand conditions improves over time is tested. As the low quality of stock data has previously been criticized (e.g. Abbott 2013; FAO et al. 2011), it is also analyzed which categories (stocks, trade, production, utilization) show the highest differences. If the differences are not mainly driven by well-documented methodological discrepancies, they can be seen as an approximation of the underlying uncertainty.

Previous studies on storage-trade cooperation have ignored private storage and a responsive supply, two key features in the analysis of price stabilization. Hence, the main research question for **chapter 3** is:

2. *How do the fiscal costs and impacts on price levels, volatility and extreme events of the following three policies compare: maintaining emergency reserves, subsidizing private storage, or strategically using trade restrictions?*

The analysis accounts for private storage and a responsive supply. Because the success of insurance mechanisms depends on the similarity of interests involved, it is further analyzed how cooperation between countries can be achieved. The impacts of policies on market agents are depicted as government interventions have continuously been reported to distort markets. These theoretical analyses are conducted with a dynamic programming partial equilibrium model with private stockholders and producers featuring rational expectations.

Private storage is an important cost-free stabilization mechanism which is typically analyzed with the competitive storage model (CSM). But this model is numerically complex and cannot be used directly to quantify private stock determinants. This leads to the main research question in **chapter 4**:

3. *How can competitive private storage be approximated by a reduced-form equation and can this equation be used to empirically validate the CSM?*

The surface response fitting of numerical results from the competitive storage model yields a surrogate reduced-form model. This can be used for direct quantification of stock determinants as well as for high-dimensional modeling exercises where it can substantially reduce the numerical complexity. Because empirical validity test of the CSM have focused on price distributions and ignored stock levels, the presented empirical validation tests are the first of its kind which account for actual stock levels.

India has one of the most ambitious public stockholding programs but suffers from surging stocks and costs. Therefore, and to evaluate options for reforms, it is crucial to understand how different policies and other factors quantitatively impact stock levels. So far, this remains a black box. Thus, the main research question in **chapter 5** reads as:

4. *How do policies and market conditions quantitatively impact India's public and private rice stocks?*

First, the economic theory of how policies are expected to influence public stocks is developed which is then tested with empirical data applying a simple ordinary least square estimation on levels and first-differences. For the first time, empirical interactions of public and private stocks are analyzed quantitatively. Chapter 4 provides the theoretical foundation for this analysis which is extended by an instrumental variable approach.

A responsive supply helps to stabilize markets and prevent crises. Yet, there is little evidence on how up-to-date farmer's price information is, even for a country like China which is still partly focusing on self-sufficiency thereby underlining the need for a responsive supply. Thus, the main research question in **chapter 6** is:

5. *How up-to-date are the price information of China's rice, wheat, and corn farmers and what are the dynamics of the production response to prices?*

A panel data set is created to assess the response over different provinces using the difference GMM estimator. Naturally, numerous control variables need to be included. As climate change is increasingly influencing agricultural yields around the world, the influence of temperatures, rainfall, and droughts on production is also analyzed.

1.3 Outline

The previous sections illustrated the importance of price stabilization policies, related problems, controversies and research gaps. The remainder of this thesis is structured in five self-contained but related core chapters which address the above-mentioned research questions and contribute to the ongoing debates and closure of research gaps. These five core chapters are followed by the general conclusion and outlook, references, and appendix. Chapters 3, 4, and 5 focus on storage and trade, chapters 2 and 6 on information.

Chapter 2 compares global corn, wheat, rice, and soy supply and demand estimates from different sources using cointegration, correlation, and granger causality tests, as well as the coefficient of variation and an extension of differences-in-differences. The quality of these estimates is assessed and underlying reasons for differences in estimations are revealed.

Chapter 3 presents a theoretical storage-trade model to compare the theoretical effectiveness and fiscal costs of international price stabilization policies. These policies aim at maintaining public reserves, subsidizing private storage or strategically using trade restrictions.

In chapter 4, a reduced-form approximation of competitive private grain storage is derived. Empirical testing of the influence of individual parameters using data from 32 countries provides support for the validity of the competitive private storage model.

Chapter 5 provides an empirical case study on rice stocks in India. Economic theory is used to derive how policies are expected to influence public stocks which is then empirically verified. Impacts of different policies reveal the need for reforms. Results from chapter 4 are used to quantify private stock determinants and crowding out effects of public storage.

Chapter 6 presents a case study for China illustrating how the supply of rice, wheat, and corn responds to prices over time. This indicates how up-to-date farmers' price information is. Additionally, weather-related determinants such as rainfall and temperatures are evaluated.

2 Different Sources, Different Information? How and Why Global Grain Supply and Demand Estimates Differ[2]

2.1 Abstract

High quality and up-to-date information is a fundamental prerequisite for an optimal allocation of resources. Yet, little is known about the quality of international supply and demand estimates. Earlier studies used within-source comparisons to test for bias and smoothing, but between-source comparisons, which allow additional analyses such as testing for differences in the processing and availability of information, are missing. This study fills this gap by comparing global grain estimates from the USDA, IGC, and FAO, all provided via AMIS, using different methods to account for methodological differences. Methods include comparing the coefficient of variation, the standard deviation of relative changes, pairwise correlation tests, cointegration analysis, and granger causality tests. Findings indicate that different sources adjust their estimates very similarly over time resulting in a co-movement. Hence, differences in data availability and processing of new information seem to be minimal. Weak evidence suggests that the FAO might be slightly slower in adjusting their data. The highest differences between sources are observed for stocks and trade and these cannot fully be explained by historical differences. It is then argued that for most analyses averaging over the three sources improves precisions and robustness of the estimation compared to taking estimates from any specific source. Finally, to really profit from the potential benefits of heaving estimates from different sources, more consistency in data collecting methods is necessary and above all better documentation of data collection and aggregation methodologies is required.

2.2 Introduction

Markets are considered to be efficient if all available information is reflected in the prices (Fama 1970). Thus, only efficient markets can exhibit an optimal allocation of resources. Another prerequisite of a sustainable and sound use of resources is the availability of up-to-date and high quality information on which different agents can base their decisions. Short-run food supply shortages can only be prevented if traders, stockholders, producers, and the government can anticipate a forthcoming crisis and react with countermeasures. If markets were fully efficient, current prices would contain all possible risks. But given that markets in

[2] An earlier version of this work was presented and internally distributed at the eight session of the global food market information group of AMIS, Milan, 19 Oct 2015, under the name "What can We Learn from the World Supply-Demand Outlook Data Published in the AMIS Market Monitor Reports?" An earlier version of the results for the coefficient of variation method was also published in the conference proceedings of the 2014 AAEA Annual Meeting, Minneapolis, as Brockhaus, J., Kalkuhl, M., "Can the Agricultural Market Information System (AMIS) Help to Reduce Food Price Volatility?"

developing countries are often incomplete and agents are rarely fully rational, it is questionable whether prices always reflect all information available (compare e.g. Antoniou et al. 1997; Zalewska-Mitura and Hall 1999). Furthermore, if little information is available, prices in efficient markets would still be a very vague (though unbiased) indicator of the supply and demand situation. Thus, the collection and dissemination of timely data of high quality about supply and demand conditions is of crucial importance to prevent food crises in vulnerable countries. Besides its importance for markets, data on fundamentals is essential for academics as countless studies heavily rely on this data.

Before the G20 conference in Cannes in 2011, many major problems in agricultural markets were identified. These included poor stock and domestic price data, poor understanding of the linkages between international and domestic prices as well as inappropriate and uncoordinated policies responses (FAO et al. 2011). The latter were often resulting from a lack of information or understanding (ibid.). Furthermore, a lack of timeliness of data provision was identified and it was noted that most data is limited to production related items but does not include information on the number of farms, agricultural households and welfare related issues (AMIS 2012b). Therefore, in the Ministerial Declaration "Action Plan food price volatility and agriculture" the Ministers expressed their concerns about the negative impacts of excessive volatility on access to food for the poorest, on producers and their production decisions, on agricultural investments, on effective market responses to long-term increases in demand for food, and on the confidence in international markets (G20 2011a). An agreement consisting of five steps was achieved: (i) improving agricultural production and productivity, (ii) increasing market information and transparency, (iii) strengthening international policy coordination, (iv) improving and developing risk management tools, and (v) improving the functioning of agricultural commodities' derivatives markets. In order to address (ii), the market information and transparency, there was consensus that an "Agricultural Market Information System" (AMIS) should be launched. AMIS was planned to "encourage major players on the agri-food markets to share data, to enhance existing information systems, to promote greater shared understanding of food price developments, and to further policy dialogue and cooperation" (G20 2011a). Thus, AMIS is not an organization, but rather a platform for exchange and cooperation. In addition to the G20 countries plus Spain, other major grain or oilseeds exporting or importing countries as well as the private sector were invited to participate. By October 2011, Egypt, Kazakhstan, Nigeria, the Philippines, Thailand, Ukraine and Vietnam were also participating (G20 2011b). AMIS is supposed to focus on the main market players and is housed at the FAO in Rome with the Secretariat including other international organizations. An analysis of the functioning of AMIS is provided by Brockhaus and Kalkuhl (2014). One of the main tasks of AMIS lies in the improvement, harmonization, and dissemination of data. Therefore, by now, access to partly but not fully harmonized datasets including estimates from different sources is available.

This study concentrates on comparing the global supply and demand forecasts from the USDA, FAO-AMIS, and International Grains Council (IGC). These are provided in the monthly market monitors published via AMIS. Both cross-source comparisons as well as within-source comparisons are conducted to analyze (i) to which extent the sources deviate from one another, (ii) how deviations evolve over time, and (iii) which categories (production/ demand/ stocks/ …) show the highest deviations. This helps to draw conclusions about the uncertainty of the data, differences in information availability and in the processing of new information between the sources, and which categories require the highest attention to improve the knowledge about the overall supply and demand situation. Earlier studies have intensively analyzed the USDA forecasts to test for bias and accuracy (Bailey and Brorsen 1998; Baur and Orazem 1994; Good and Irwin 2006; Isengildina 2004; McKenzie 2008; Sanders and Manfredo 2003), usually finding that USDA forecast are of high quality. It was further shown that the USDA forecasts are news for the markets (Good and Irwin 2006; Sumner and Mueller 1989) despite being smoothed (Isengildina et al. 2006) and that this smoothing is partly anticipated by the market (Isengildina et al. 2004). Yet, all such studies use within-source comparisons. Within the U.S., between-source comparison focusing on comparing forecasts through price reactions and in one case by directly comparing production forecasts have been conducted (Egelkraut et al. 2002; Garcia et al. 1997; Sumner and Mueller 1989). With one historical exception (Paulino and Tseng 1980), between-source comparisons of estimates on fundamentals outside of the U.S. have not been conducted. Nowadays, the study by Pauline and Tseng (1980) cannot be regarded as representative anymore as data coverage has increased, data collection and aggregation methods have changed, and harmonization efforts have been undertaken (AMIS 2012a). In addition, this study differs to Paulino and Tseng (1980) in that it compares the evolution of forecasts over time (rather than only final estimates), focuses more on differences between categories, and is more careful by only comparing data which is based on the same marketing year definition. For these reasons, only global estimates can be compared and only specific crops and categories can be included in the comparison. Visualizing how estimates from the different sources evolve over time directly leads to the main hypothesis stating that there is a co-movement between the sources (Figure 2.1).

Comparisons are conducted with different methods, the coefficient of variation (CV), the standard deviation of relative first differences which can be regarded as an extension of a difference-in-difference procedure, pairwise correlation tests, cointegration analysis, and granger causality tests. Major findings include that forecasts evolve very similarly over time indicating an akin availability and processing of information. Furthermore, results show that differences are large for stocks and trade but small for production and utilization. This highlights the need to particularly improve data collection and methods for stocks and trade. Differences between USDA and IGC data are smaller for some crop-category combinations than differences between USDA and FAO or IGC and FAO. Granger-causality tests provide weak evidence suggesting that the USDA and IGC might be providing slightly more up-to-date estimates than the FAO.

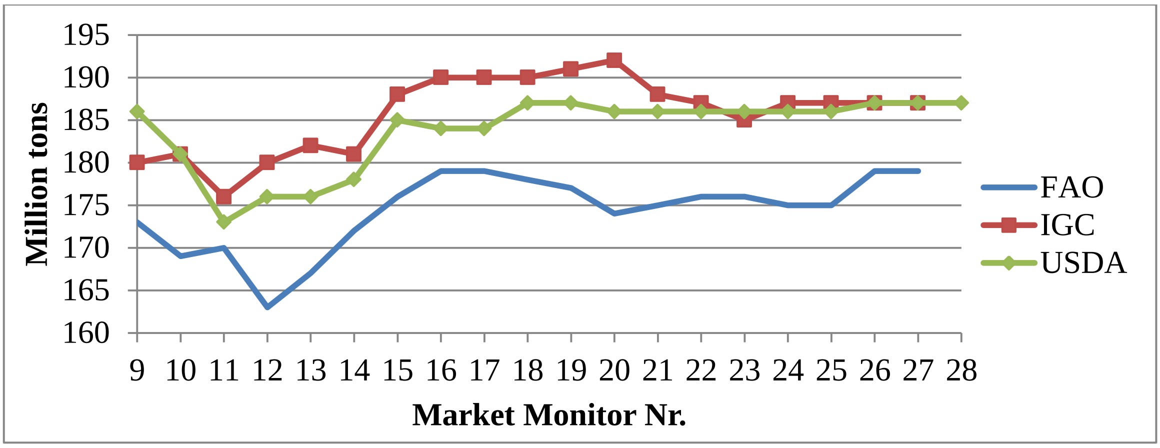

Figure 2.1: Wheat stock estimations for the marketing year 2013/2014

Note: Own illustration. Raw data from AIMS.

For various reasons, having estimations by different source is very valuable. First, they may provide different or complementary information if, for example, they use different data collection methods or different definitions of products or categories. Second, different sources may cooperate to exchange knowledge and experiences to improve the data collection process which is one of the purposes AMIS was designed for. Third, a healthy competition between the sources may drive improvements and innovation. However, the benefits of multiple estimates can only be achieved if a clear documentation of data is available. While the USDA provides a precise documentation for most of their data (e.g. USDA 2012), documentation of FAO and IGC data is scarce and incomplete. Furthermore, each source needs to apply inherently consistent methods to build their estimates. This is currently not always the case. The marketing years, for example, are sometimes defined differently (Abbassian 2015; Paulino and Tseng 1980; USDA 2012) while they should always start with the beginning of the main harvesting season. Otherwise, the so called “ending stocks” are not actually ending stocks but quantities remaining in the market at some more or less arbitrary moment during the marketing season. In that case, they cannot be compared and contain much less information about the supply and demand situation. Furthermore, other methodological differences exist. Data collection methods differ, for example, stocks can be calculated as a residual or from surveys (Abbott 2013), or product definitions may include only raw products or also processed goods. For wheat, the FAO only reports raw wheat whereas the USDA also includes processed products (Abbassian 2015). The FAO-AMIS data, which is used in this study, largely relies on statistics provided by the individual countries, although corrections may be made based on additional insights (ibid)[3]. In contrast, the USDA is known for making more substantial adjustments to official country statistics when these are regarded implausible (e.g. Paulino and Tseng 1980).

The remainder of this chapter is organized as follows: Section 2.3 delineates the data. Section 2.4 describes the applied methods and how these can capture methodological discrepancies between the sources. The results of the various approaches are presented in section 2.5. In section 2.6 it is argued that the average value of the estimates from the three sources is expected to be a better approximation of the real value than any individual estimate. Thus, the use of the mean value may be preferable in most analyses. Eventually, section 2.7 concludes.

2.3 Data

Only global estimates, not country-specific estimates, from the FAO-AMIS, IGC, and USDA are compared. The reason is that only the global estimates receive nearly monthly and largely harmonized updates for all sources and therefore allow a comparison of the evolution of estimates, i.e. how estimations change over time. In contrast, country-specific estimates are typically only available ex-post and only in their latest version. Only for very few countries there are monthly estimates and even these are not provided by all sources. As a result, the comparison is limited to global demand and supply data.

Global estimates were collected for wheat, corn, soy, and rice from the regularly forthcoming AMIS Market Monitor (AMIS 2015) Nr. 2 to 29. The provided and collected categories include production, supply, utilization, trade, and ending stocks. The data goes from 2012, the time when the database was set up, to 2015. The definitions of marketing years are drawn from Market Monitor Nr. 29 (AMIS 2015). Hence, each crop-category-year combination constitutes one time series such that overall a panel dataset with up to 100 time series is obtained, containing between 1 and 21 observations. There are 1184 observations in total, resulting in an average of about 12 observations per time series. However, dependent on the method, a substantial share of the time series needs to be dropped. Time series with few observations need to be dropped for most methods. Various consistency tests are performed. In particular, three criteria are used to identify mistakes: Outliers within one source are regarded as mistakes if (i) earlier and later values are very different and themselves very coherent, i.e. only one value deviates substantially from the otherwise inert time series; (ii) if no corresponding correction in other sources is observed, i.e. one source suddenly shows a large shift while other sources provide nearly unchanged estimates; (iii) changes within a source are inconsistent, i.e. the balancing equation *supply = production + last year's ending stocks = utilization + this year's ending stock* is not fulfilled. Based on these criteria, 14

[3] Official FAO data which is provided by the FAO directly and not via FAO-AMIS is copied from country statistics without making any adjustments.

mistakes are identified in the data and these are corrected as described in the appendix, section 8.1. In addition, a graphical visualization is provided which might allow a more intuitive understanding. These mistakes have partly been confirmed by AMIS and later on corrected in the corresponding database.

As explained in the introduction, various methodological differences exist between the three sources. Data which refers to different marketing year definitions is not compared as no method allows accounting for this difference and hence it would remain unclear what drives deviations between the sources. Other differences can be accounted for by different methods. If the only differences lie in the method of data collection (e.g. surveys versus residual estimation) these do not cause any problems. If instead different product definitions are applied, e.g. raw products versus raw plus processed products, these will result in relatively constant offsets between the sources. The same would apply if the definition of categories differs. Deviations in stock data are partly attributable to historical differences, i.e. differences for the very first stock estimations when the databases were set up which are now carried forward from year to year (Abbassian 2015). However, with the exception of differing marketing years, all these differences can be accounted for by applying appropriate methods to compare the data as explained in the following section.

2.4 Methodology

Forecasts or estimates can be seen as a function of the information available at a specific point in time. The function is then the mathematical description of how the data is processed. From that perspective, it can be tested whether sources employ different methods and/or if they have different information at their disposal. If the available information sets are different, it is to be expected that the information which is used for the final estimate[4] from different sources is more similar than information used for early forecasts, e.g. forecasts from before the respective marketing year has even started. This implies that sources update their information and are able to decrease the level of uncertainty, thereby reducing differences in the available information sets. Therefore, it would be expected that the estimations approach each other over time. While this does not imply that different sources converge, it implies that deviations are expected to decrease. If the available information is the same or comparable but different methods of data processing or aggregation are applied, this is expected to result in a co-movement of the estimations. To illustrate this, two examples are provided. First, if stock deviations are caused by historical differences which are then carried forward year to year as explained above, this results in an absolute difference which is persistent over time. However, it does not lead to differences from one estimation to the next, i.e. estimates for the same

[4] The final estimate is the last estimate for a specific marketing year, i.e. afterwards no more adjustements are made to this data.

marketing year which are provided in subsequent Market Monitors. As the second example, deviating product definitions are considered which differ in the way that one source only includes raw products whereas another source also includes some processed products. In this case, these methodological differences result in certain differences between estimations. But as time passes, these deviations are expected to remain relatively constant because the processed products are usually expected to scale with the raw products on such short time horizons where long-term trends only have a very limited influence. Hence, this approach helps deduce whether deviations between the sources are primarily a result of different methods or of differences in the information available.

Different methods are applied to compare data from the three sources. First, the coefficient of variation (CV) is calculated between the sources. This measure compares the absolute values of the estimations. Second, the standard deviation of relative changes from one market monitor to the next is calculated. This measure can be regarded as a modification of the difference-in-difference procedure. While the difference-in-difference measure can only compare two sources, the standard deviation of the first differences can compare all three (or even more) sources at once. Furthermore, instead of using the absolute first differences, the relative first changes (increases or decreases in percent) are taken because methodological differences are expected to scale relatively but not absolutely. In the example considered above where one source only considers raw products whereas another also includes some processed goods, the second one will naturally provide higher estimates. If both sources then receive similar new updates, i.e. information sets, about production increases, then this should also lead to a bigger absolute increase for the second source while, as a rough approximation, the relative increase is expected to be similar. Therefore, this measure is labeled as “standard deviation of relative changes”. However, as deviations are typically not very large, this procedure only yields minor differences compared to taking the absolute first-differences.

Third, the pairwise correlation between the individual time series is calculated. For this, each crop, category, and marketing year combination is regarded as its own time series. Fourth, a cointegration analysis is conducted in two ways. On the one hand, the Engle Granger cointegration tests are applied to each pair of time series (Engle and Granger 1987; critical values from MacKinnon 2010). On the other hand, a panel cointegration method is used (Westerlund 2007). Calculations are performed in Stata with the xtwest command (Persyn and Westerlund 2008) including the bootstrapping option to account for dependencies across categories. The correlation coefficients indicate how similar individual adjustments (updates) are, whereas the cointegration statistics shed some light on how the time series are bound together, i.e. experience similar long-term time trends. Short-run deviations are allowed but in the long run it is expected that a dependency between the variables persists (compare to error correction models, e.g. in Engle and Granger 1987; Westerlund 2007).

Granger causality test are conducted to analyze if there is a source which moves earlier or later than the others. This would indicate that this source uses more or less recent information. However, the release dates of the estimates from the different sources differ (AMIS 2015) which naturally leads to differences in the available information sets. Therefore, findings of this test have to be treated with great caution and could also merely be a reflection of different release dates.

Besides comparing differences between the sources, adjustments within each source are measured and compared by simply calculating the coefficient of variation between the respective estimate under consideration, i.e. the current projection, and the final estimate for that marketing year. This illustrates the extent to which adjustments are made and how adjustments differ between the sources.

For the first two measures, the CV and the standard deviation of first differences, a set of time series rather than just two or three individual ones are compared. Then, the measures are applied as explained above, followed by taking the averages over different groups. For example, this implies that to compare deviations between different crops and categories, these are calculated individually for each marketing year and then the averages over different marketing years are built. Similarly, to compare the evolution of estimates for specific categories, the averages of the results from the different crops and sources are taken. This procedure allows the inclusion of more observations and improves the robustness of results.

2.5 Results

First, the differences in absolute values of the estimations for different crops and categories are compared (Figure 2.2). The average CV on the y-axis (Figure 2.2) is the average of the CVs calculated for the different marketing years. It can be interpreted as a measure of how different the sources are (in absolute terms). For many items, the marketing year definitions are different and as a result, only those that do not differ are compared. It turns out that some differences between the crops exist, but most importantly, the ending stocks and trade data seem to differ more from one another. Comparing only two sources instead of all three allows the comparison of more crop-category combinations because of fewer differences in the marketing year definitions (Figure 2.3)[5]. The observed pattern remains as before, i.e. differences between the ending stocks and the trade data are huge whereas deviations in production data are low. The differences in supply data are mostly driven by last year's ending stocks. Differences for utilization are very crop-dependent but are mostly below those of the ending stocks or trade data. The differences between the crops seem to be comparable.

[5] The FAO and USDA use the most different marketing year definitions while the IGC sometimes overlaps with the FAO and sometimes with the USDA marketing year definitions.

Very similar results are obtained by comparing the data with the second measure, the standard deviation of relative changes. For both, the comparison of all sources (Figure 2.4) as well as the comparison of only two sources (Figure 2.5), it is found that the deviations are very high for ending stocks and trade whereas only minor differences are observed for production, supply, and utilization. Hence, not only do the absolute values in these categories differ greatly, but their changes when updates are made also differ substantially. This underlines the need to improve data collection methods for these categories. Earlier studies have found similar results and criticized the poor quality of data on trade (Paulino and Tseng 1980) and stocks (Abbott 2013). Besides comparing how changes differ from one Market Monitor to the next, the deviations of changes from one marketing year to the next are analyzed with the same measure and yield the same results (Figure 2.6). The differences for ending stocks and trade data are found to be very high, whereas differences in other categories are comparably low.

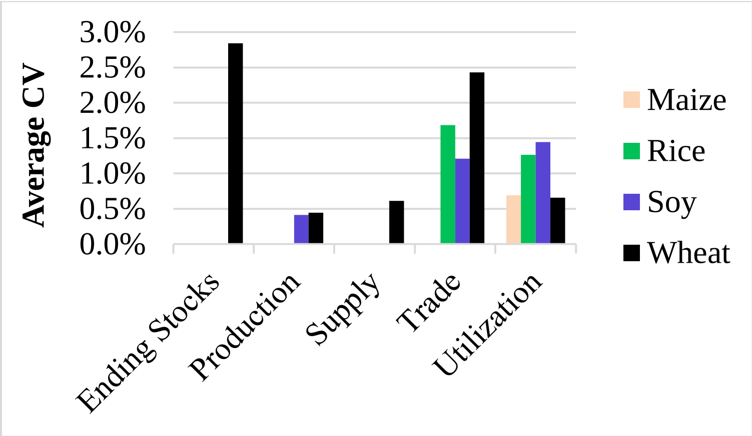

Figure 2.2: Comparison of absolute values between all sources (Own illustration)

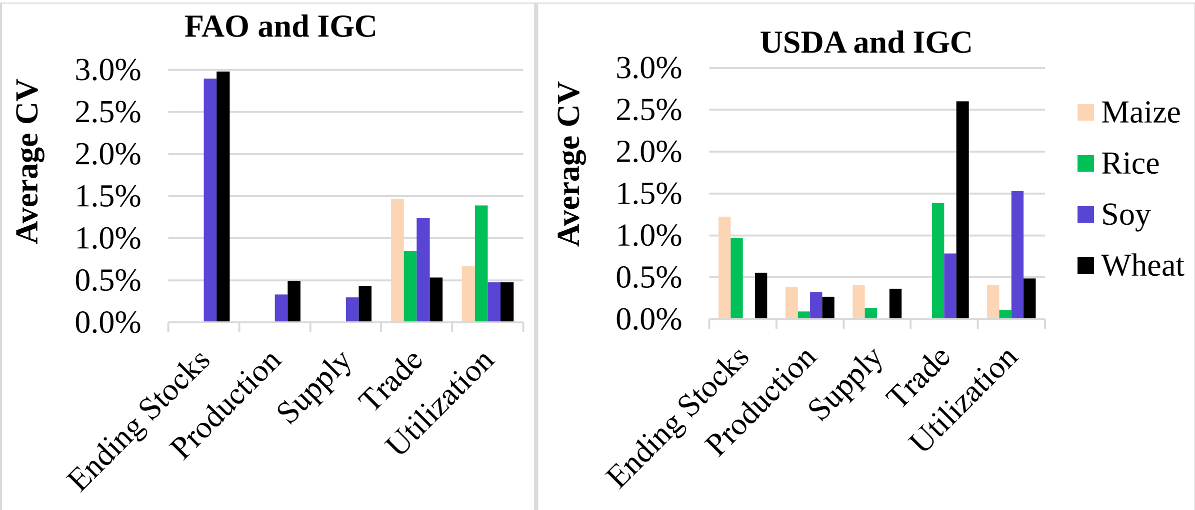

Figure 2.3: Comparison of absolute values between two sources only (Own illustration)

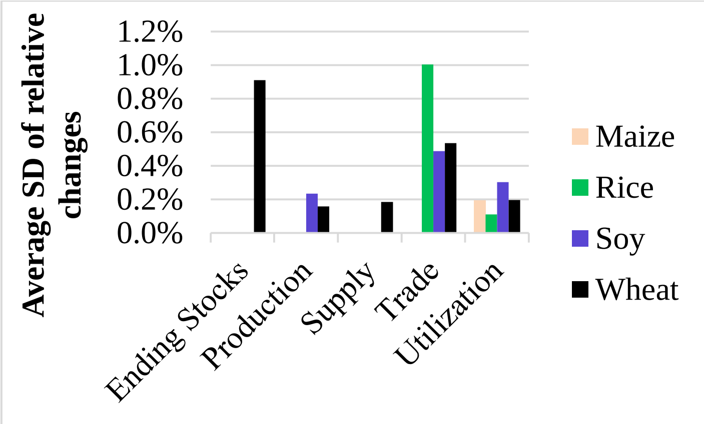

Figure 2.4: Average SD of relative changes between all sources (Own illustration)

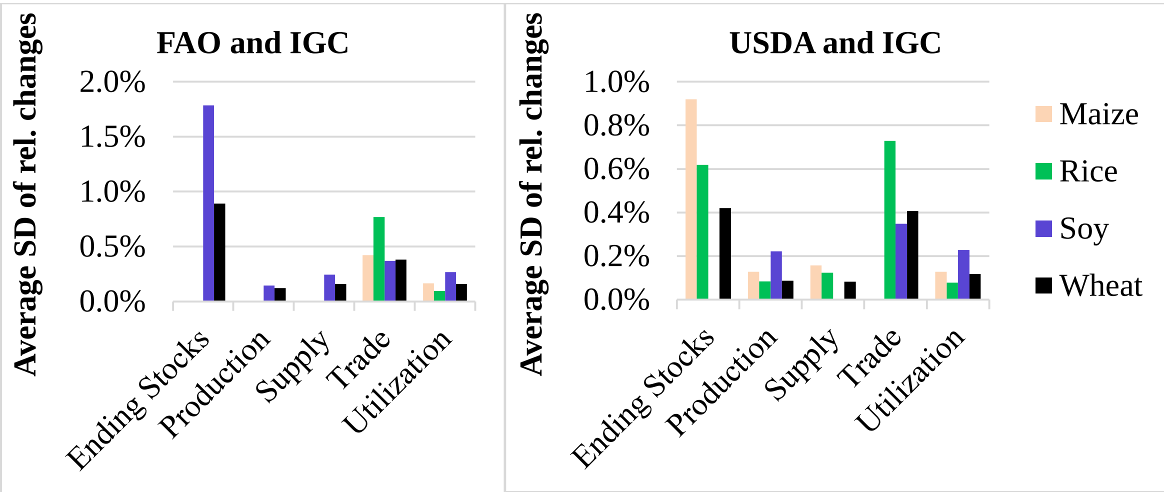

Figure 2.5: Average SD of relative changes between two sources only (Own illustration)

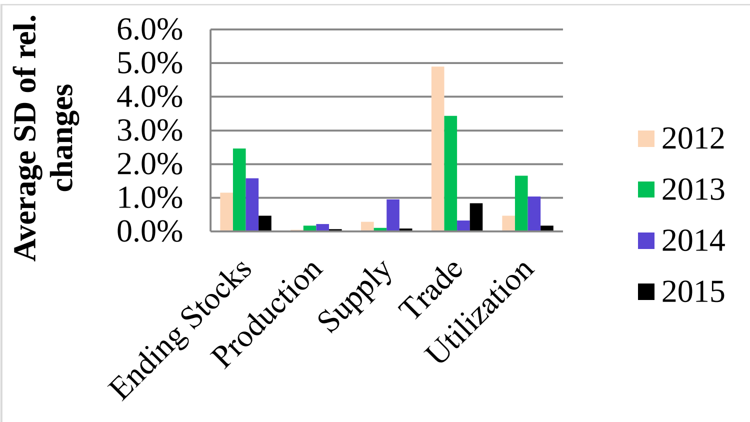

Figure 2.6: Average SD of relative year-to-year changes (wheat only) (Own illustration)

By comparing the adjustments over time within each source, one can infer whether there are differences in the adjustments between sources. The estimations for each marketing year are tracked over time and the CV of the current estimate with the final estimate for each crop-category combination is calculated before building the average CV over all crops and categories (Figure 2.7). In contrast to the between-source comparisons, data on all crops and categories can be used for these within-source comparisons. Several conclusions can be drawn. First, unsurprisingly, early forecasts exhibit a substantial deviation from final estimates but these differences become smaller over time. Second, for the individual marketing years, corrections in the first Market Monitor releases are larger than corrections made in the last editions which report values for that year[6]. Hence, early forecasts suffer from a very high uncertainty but this reduces rapidly at the beginning. Third, the individual sources seem to follow a similar trajectory over time. Thus, no source is faster than the others in reducing the differences to their final values. In individual years, this may not be true[7] but overall there is no clear indication that any source performs better by this measure.

To illustrate how the adjustments differ by category, the individual categories are illustrated in a separate graph (Figure 2.8). Again, a decline of the differences over time can be observed. While the initial average CV for data on production, supply, and utilization is about 1%, it reaches up to 3% for data on trade and even up to 7% for stock data. As a result, it seems that the sources make major relative corrections to the stocks and trade estimates whereas the other estimates remain almost untouched in relative terms. As the amounts produced, supplied, and utilized are much higher than those traded and kept in stock, the absolute adjustments might behave differently.

For wheat and soy, there are enough comparable categories to track the differences between the three sources over time (Figure 2.9). Results show that the differences between the sources are relatively stable over time, in particular, no convergence and more or less no approximation can be observed. In comparison to the graphs showing how the sources adjust their own estimations over time (Figure 2.7 and Figure 2.8), the differences between the sources are smaller than the differences within the sources when early and late estimates are compared. For data on stocks and trade, the adjustments made over time are larger than the differences between the sources. Yet, despite these relatively large adjustments, estimates from different sources do not approach each other. These results imply that there is a co-movement between the sources. In other words, the different sources update their estimations in a similar manner. If one source increases or decreases their estimates, the other sources follow. However, at this stage it remains unclear how fast the sources follow each other. Following the explanations in section 2.4, it can be concluded that methodological differences between the sources exist but the information available to the different sources and the way of incorporating new information seems to be very similar. Relatively constant differences

[6] Note that the series for 2011/12 and 2014/15 are incomplete. Early estimates are missing for the former while late estimates have not yet been available at the time of writing for the latter. Thus, this result is drawn from the observations for the marketing years 2012/13 and 2013/14 only.

[7] The FAO more quickly reduced the deviations from their final estimates in 2012/13, for example. However, in 2014/15 the FAO performed relatively poor by this measure.

between the sources, possibly a result of different aggregation methods or product definitions, are carried forward over time but remain mostly unchanged.

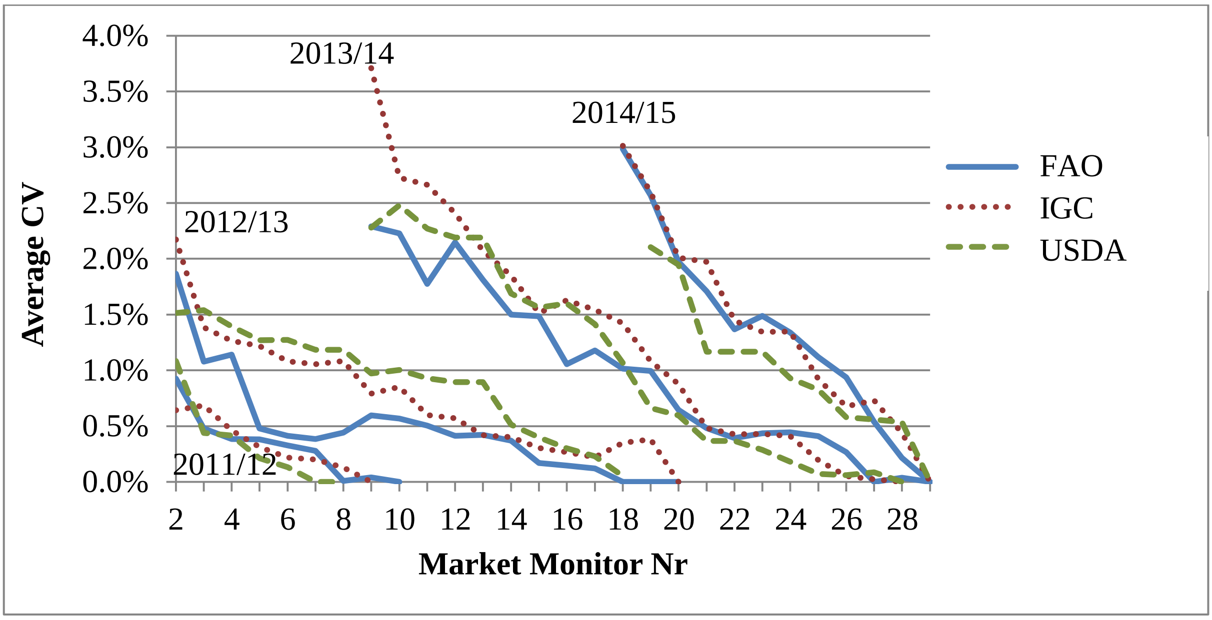

Figure 2.7: Adjustments of estimations from all sources over time (Own illustration)

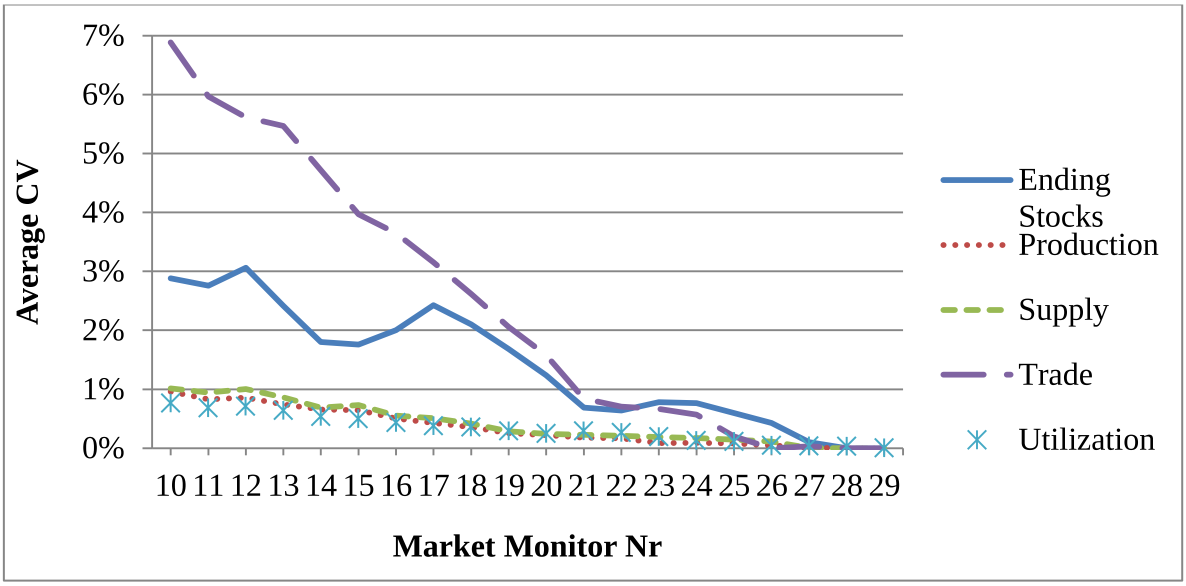

Figure 2.8: How adjustments differ by category

Notes: Own illustration. Only marketing year 2013/14 is displayed because taking the averages over different marketing years might wipe out the effect as early and late estimates would be mixed. Averages are taken over the different sources and crops but similar graphs are obtained if only individual sources or crops are depicted.

For wheat, it is even possible to track the difference between all categories over time (Figure 2.10). This confirms earlier observations. No trend indicating that estimates approach each other over time can be identified. Even though this may happen for specific years and categories, counter-examples are numerous. Trade data became much more similar in recent years, i.e. for the marketing years 2014/15 and 2015/16. This means that from one marketing year to the next the trade data improved but not within the individual marketing years. This behavior could potentially indicate that harmonization efforts were undertaken at that point in time. Global stock data, however, did not improve over time for the considered time period from 2012 to 2015. However, it may have improved on a longer time horizon.

Correlation, cointegration, and granger causality test are performed to underline previous results and obtain further insights from the data (Table 2.1). All three methods can be applied to each pair of time series; however, different minimal lengths of the time series are required. For all pairs of sources, a large share of the time series is found to be correlated. The mean level of correlation amounts to roughly 0.6, which highlights how similar the sources process new information. The correlation between the USDA and IGC is slightly higher than between the other pairs indicating that these sources change their estimates in an even more similar manner.

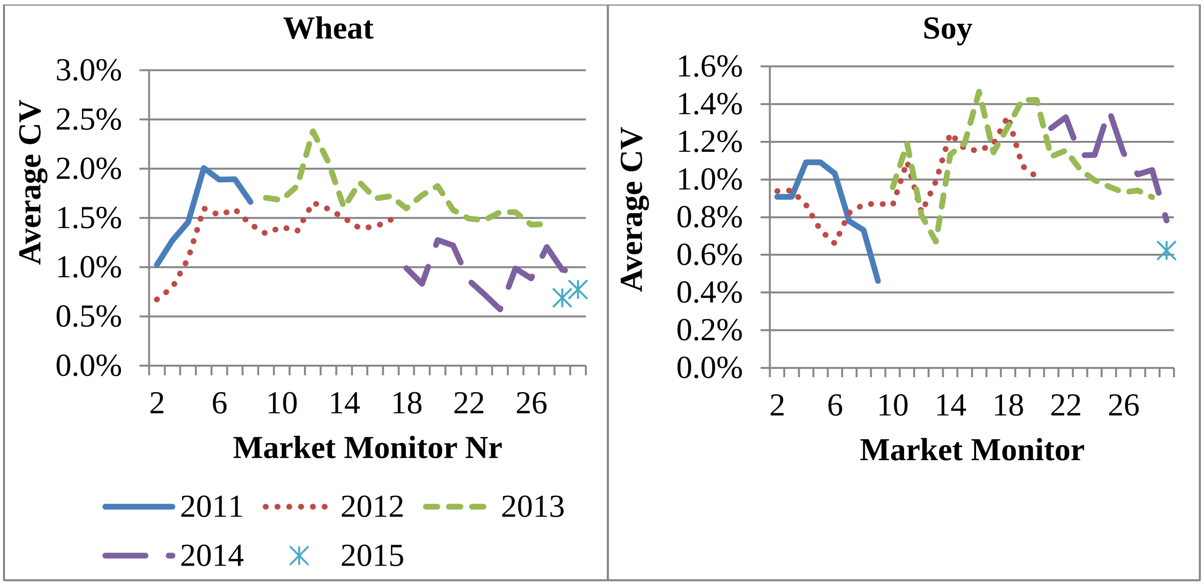

Figure 2.9: Differences between the sources over time for wheat and soy

Notes: Own illustration. The averages over different categories are taken. For wheat, all categories are used whereas only the production, trade, and utilization are used for soy because only these categories are comparable between all sources. Hence, no conclusions can be drawn from this graph about whether differences for wheat are larger than for soy. Years in the legend, which are the same for both graphs, refer to the first year of the marketing season.

Pairwise cointegration analysis shows that more than 25% of the pairs of time series between the sources are found to be cointegrated using the 5% threshold and around 15% using the 1% threshold (Table 2.1). Cointegration between FAO and USDA is slightly higher than between the other pairs which might indicate a more similar trend between these sources. As a further robustness check, the panel cointegration tests which compare all time series from a pair of sources at the same time are also performed. The two different group-mean tests Gt and Ga test the null hypothesis that all coefficients of explanatory variables are zero against the hypothesis that at least one coefficient is different from zero (Persyn and Westerlund 2008). Thus, rejection of the null hypothesis is evidence for cointegration of at least one cross-sectional unit (ibid.). The two different panel tests Pt and Pa test again the same null hypothesis of all coefficients being zero against the (fundamentally different) alternative that all coefficients are different from zero. In this case, rejection of the null hypothesis is evidence that the panel is integrated as a whole. Accounting for heteroscedasticity, all three pairs of panels are found to be cointegrated at the 1% level by all four test criteria. This provides strong evidence that the sources follow very similar trajectories. Therefore, the earlier finding that different sources apply different methods but have access to similar information sets and process new information in a similar manner is further supported by these results.

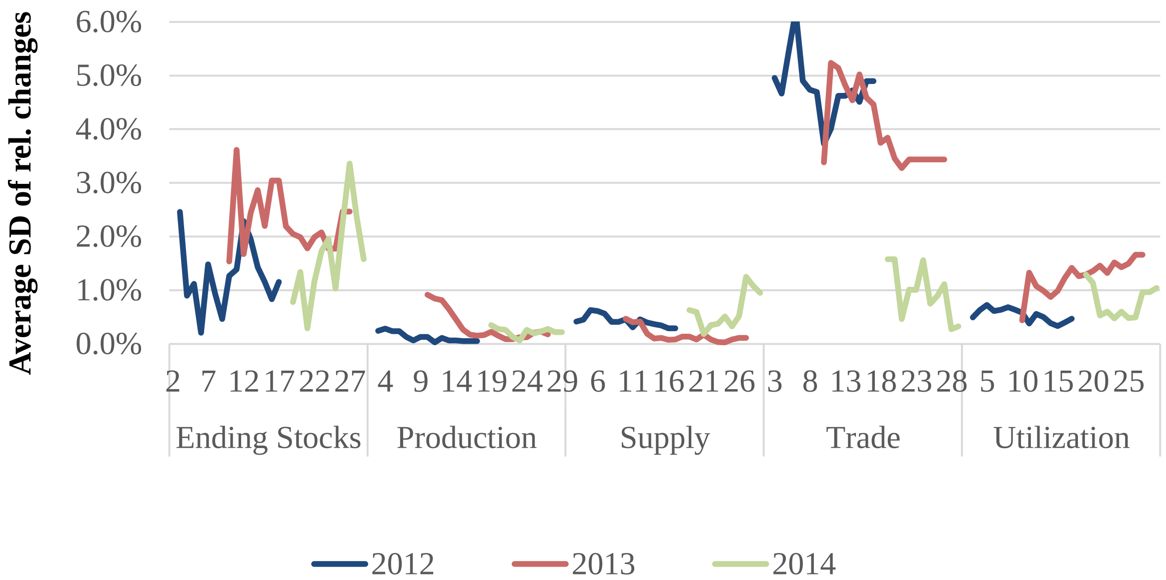

Figure 2.10: Evolution of category-specific differences between sources for wheat

Notes: Own illustration. For each category, the time evolution over the Market Monitors is shown on the x-axis. Years in the legend refer to the first year of the marketing season.

Table 2.1: Correlation, cointegration, and granger causality tests

	IGC–USDA	IGC–FAO	FAO–USDA
Pairwise correlation			
25th percentile	0.53	0.39	0.42
50th percentile	0.82	0.69	0.7
75th percentile	0.9	0.84	0.87
Mean	0.67	0.54	0.57
Standard deviation	0.35	0.46	0.41
N (# of time series)	44	44	44
Min/Mean/Max observation per time series	7/13/19	7/13/19	7/13/19
Pairwise cointegration			
Share of series cointegrated at 1% threshold	14%	14%	18%
Share of series cointegrated at 5% threshold	25%	27%	32%
N (# of time series)	44	44	44
Min/Mean/Max observation per time series	5/11/17	5/11/17	5/11/17
Panel cointegration			
Robust p-value for Gt	0.000	0.005	0.005
Robust p-value for Ga	0.000	0.000	0.000
Robust p-value for Pt	0.000	0.000	0.000
Robust p-value for Pa	0.000	0.000	0.000
N (# of time series)	19	22	19
Min/Mean/Max observation per time series	17/19/21	17/19/21	17/19/21
Pairwise granger causality			
Share of series showing forward granger causality at 1% threshold	32%	43%	40%
Share with forward granger causality at 5%	39%	54%	61%
Share with backward granger causality at 1%	32%	25%	50%
Share with backward granger causality at 5%	43%	36%	64%
N (# of time series)	28	28	28
Min/Mean/Max observation per time series	9/14/17	9/14/17	9/14/17

Notes: Own illustration. Except for the panel cointegration, all statistics are calculated pairwise, i.e. for each pair of time series. Methods impose different restrictions on the number of time series and observations which can be used. Granger causality is tested forward, i.e. if the source mentioned first in the table header granger-causes the second, and backward, i.e. if the source mentioned last in the table header granger-causes the first; in both cases for the 1% and 5% threshold and with the first and second lag. Panel cointegration uses 200 bootstrap repetitions, a kernel window of three, and one or two lags and leads based on the Akaike information criterion.

Pairwise granger causality tests show that the sources partly granger-cause each other (Table 2.1), i.e. some series of each source granger cause some series from another source. Both directions of granger causality are tested. For the USDA and IGC data, they yield a comparable share of time series pairs which are found to granger-cause each other at both the 1% and 5% threshold. For other pairs of sources, shares are comparable but not as similar. First of all, this finding of granger causality in both directions is further support for the discovered co-movement between the sources. When comparing the IGC-FAO results and the FAO-USDA results for forward and backward tests, it becomes clear, that many more FAO series are granger-caused by IGC data and slightly more by USDA data than the other way round. This is not a mere reflection of different release dates as the FAO estimates are calculated after the USDA and IGC estimates from the same Market Monitor (AMIS 2015). Indeed, the USDA estimates from the same market Monitor are roughly calculated three weeks earlier than the FAO estimates. This indicates that it might be equally justifiable to shift the USDA data forward by one period (Market Monitor) for the granger causality tests. With this shift, even more USDA series are found to granger-cause FAO series than the other way round (64% versus 50% at the 5% threshold and 46% versus 36% at the 1% threshold). As a result, there is mild evidence that the IGC and USDA adjust their estimates earlier than the FAO-AMIS which might indicate that they use more up-to-date information or are faster in processing information. However, as the differences in the shares of series showing forward and backward granger causality are not very big, this result has to be interpreted with great caution and further analyses should be conducted to shed more light on this issue.

2.6 Creating own estimates based on USDA, FAO, and IGC data

The results of the previous section show that there is no source which provides significantly better estimates than the other sources. Thus, no a priori recommendation to use data from a specific source can be made based on this analysis. However, if it is of crucial importance to apply the most recent data, then the USDA and IGC data might be slightly superior as the analysis provided some weak evidence that these sources are slightly more up to date. However, it is possible to construct own estimates from the USDA, FAO-AMIS, and IGC data which in many cases may be superior to the data from each individual source. As no source is superior, it is the best to simply take the mean value from all three sources. This is a very simple operation and the effort of acquiring the data is therefore very limited. The average values for the data included in this analysis are presented in Table 8.1 in the appendix (except for the year 2015, where there was hardly any data at the time when the analysis was conducted). Taking the mean values of the three sources has a number of advantages compared to taking the values from one specific source.

First of all, the mean is less prone to mistakes in the data. Mistakes can happen for all sources and as shown in appendix 8.1, presumptive mistakes are found in all data sources. In any econometric analysis, such mistakes can have huge impacts. For regressions, an outlier which differs substantially from the other data points can have tremendous impacts on the estimated coefficients. Taking the mean values does not fully solve this problem but it reduced size of the outlier as the two correct sources help to keep the mean value in line with the rest of the data. Therefore, the effects of mistakes in the data on estimated coefficients are substantially reduced.

Second, for the same reasons, the mean value is less prone to individual estimation errors. If any source does not account for all available information, they may be higher or lower than they should be. This problem is reduced if the mean of the sources is taken.

Third, the specific methodological differences between the sources are mostly undocumented. Therefore, a researcher or any other interested person cannot judge which methodology suits best to the intended way of using the data. If the precise methodological discrepancies were known, one could choose which data fits one’s needs best. But as they are unknown, it may be better to build the mean value, i.e. the average over the different methodologies. While a specific (but unknown) source may be better, this procedure reduces the influence of the specific data collection and aggregation methodology on the results. If a specific source were chosen randomly, taking the mean would not reduce the expected influence of the specific methodology of this source, but it reduces the likelihood to pick the most inappropriate source. Hence, the results are expected to be more robust. Therefore, this procedure can be seen as a risk-averse approach to select input data, i.e. the expected bias is not reduced, but the maximal possible bias is.

Fourth, if the sources are trying to measure exactly the same things (due to different methodologies this is not fully clear), then the cumulated information is usually better than the information from each individual source (Acemoglu and Ozdaglar 2011; Galton 1907; Surowiecki 2004). Thus, the mean is expected to be a more precise estimate than any individual estimate from one of the sources. However, this “wisdom of crowds” effect can be undermined if the errors from the sources are not statistically independent, external influence is exercised, or other “distortions” exist (Lorenz et al. 2011; Vul and Pashler 2008). Yet, the expected maximum deviation from the real value would still be reduced by taking the average from all sources.

Overall, these factors suggest that the mean is a better approximation of the real value than the individual estimates. Furthermore, it can help to improve the robustness of results which are based on such data by reducing the impact of mistakes, inappropriate methodologies and estimation errors. Table 8.1 in the appendix presents the mean values for the data in this study. This procedure works well on the global level, but it may be inadequate for individual countries because the different sources apply different and sometimes inappropriate marketing year definitions for some countries.

2.7 Conclusion

Testing whether markets are efficient is among the research questions which have attracted the highest academic interest due to the importance of market efficiency for the allocation of resources. However, efficient markets are not sufficient; high quality and up-to-date information also needs to be available for sustainable investments, crises prevention, and resource allocation in general. Yet, knowledge about the quality of grain supply and demand estimates is limited. While different studies have used within-source comparisons to analyze bias, smoothing, and accuracy, there is a lack of studies comparing data from different sources (the notable but historic and methodologically more limited exception is Paulino and Tseng 1980). This study fills remaining gaps by providing between-source comparisons using four different measures: the coefficient of variation, the standard deviation of relative first-differences (a diff-in-diff extension), correlation coefficients, and cointegration analysis. These different methods are useful because they allow accounting for different methodological discrepancies between sources as well as addressing different research questions. However, data is not compared if marketing years are different because accounting for such a distinction is not possible. Furthermore, granger causality tests are performed to test for lead and lag sources. For the first time, the evolution of different estimates over time is tracked and compared.

Results show that over time the FAO-AMIS, USDA, and IGC adjust their global grain supply and demand estimations in a very similar manner. This leads to a co-movement of estimations over time. Differences in the estimations seem to be driven by methodological discrepancies rather than differing information. For data on stocks and trade, the differences are particularly large, independently of whether they are compared in absolute terms or as relative changes. Production estimates are comparatively similar. Weak evidence suggests that the USDA and IGC estimates are slightly more up-to-date than the estimates by FAO-AMIS.

Furthermore, it has been shown that using the mean value of the estimations from the different sources may provide several advantages over taking the estimates from any specific source. This procedure can make the results more robust as it reduces the impact of mistakes, estimation errors, and potentially not fully appropriate methods of data collection and aggregation. In addition, the mean value has been argued to typically be a more precise approximation of the "real" value than any individual estimate.

If monthly updated estimates for the individual countries were available, the same analysis could be conducted for all countries and it could be identified which countries drive the differences between the sources. However, while monthly updated forecasts are not available, the final historical estimates are available from all three sources. These haven been analyzed by Brockhaus and Kalkuhl (2014) and it was shown that the largest differences occur for

Nigeria, Turkey, India, Viet Nam, Indonesia, and the Philippines whereas the US data was the most similar.

Seven policy conclusions can be drawn from this analysis:

(1) Documentation of data, in particular on data collection and aggregation, urgently needs to be improved. For most of the data provided, it remains unclear how exactly data was collected and aggregated and what input information was used (prices, weather data …). Even acquiring knowledge about basic specifications such as the definition of marketing years sometimes requires extensive research efforts. Furthermore, better documentation could provide insights about the extent to which differences between sources are driven by the balancing out of total supply and demand.

(2) Being the only initiative of its kind, AMIS is of crucial importance for discussing and harmonizing methods between sources, providing a platform for exchange, and increasing the data collection capabilities. Substantial progress has been made in this area, including the recent launch of a policy database on the AMIS website. However, the low level of funding that AMIS receives needs to be addressed (Fiott 2011)[8] and AMIS still has to augment pressure on national governments, in particular on those of large emerging countries, to increase the amount of information collected and to expand the extent to which this information is shared (argument in line of Gilbert 2011b). To date, several countries do not even manage to report their data to AMIS according to the defined time schedules (AMIS 2013; Paquotte 2015). Kazakhstan, Nigeria, and Saudi Arabia have been reported to not having delivered any data in the past while data from many countries including India, China, Thailand, and Vietnam has been criticized for being incomplete (AMIS 2013). Apart from that, based on the findings, no overall improvement of data quality over time can be observed.

(3) Results show that the information available to the sources seems to be mostly comparable but that differences are likely to be an outcome of different methods. Further harmonization would allow better comparisons and thus less uncertainty about the agricultural supply and demand situation.

(4) Findings highlight that more attention is needed to improve the data on stocks and trade, whereas production estimates seem to be experiencing less uncertainty.

(5) In some cases, more consistency is required. This is the case if the marketing year does not start with the harvest of the main crop leading to large "ending stocks" which are a reflection of stocks somewhere in the midst of the season. Another example is the FAO trade data where the total exports do not always match the total imports for each year but they are only balanced out over several years.

[8] Funding from FAO for the AMIS website is also ending in 2015 and needs to be replaced by the countries (Abbassian 2015).

(6) A very unsatisfying historic artifact that requires attention are differences in stock estimates for the time when the databases were set up. These are now carried forward from year to year for those sources which estimate stocks as a residual. In this case, an actual estimation of current stock levels followed by an adjustment of historical stocks (e.g. by updating stocks with the help of supply-demand balances) may provide a more satisfying solution as data on stocks has probably improved during the last decades.

(7) All sources should provide more details on underlying reasons for updates of data (argument in accordance with Paquotte 2015). To date, in many cases some qualitative information is provided, but how individual factors quantitatively lead to updated estimates remains a black box. This would also allow a better understanding of differences between sources.

(8) By providing more disaggregated data, the sources could draw a clearer picture about the supply and demand situation and would allow researchers to use datasets which are more adjusted to their needs. For example, a distinction between raw products and processed goods should be made by all databases. Recently, efforts have been undertaken to include an increasing amount of not officially documented trade in the databases (Abbassian 2015), but unfortunately no such distinctions are made in the data provided on the AMIS website.

The main limitation of this study results from the methodological discrepancies between the sources. Five different methods were used to account for these differences. However, there may be unknown methodological differences which are therefore not fully accounted for by the chosen methods. In addition, evidence on some of the results (e.g. the granger-causality test) is weak, partly because there are no applicable statistical significance tests available.

Further research should provide evidence on whether (and if so, why) the FAO-AMIS is slower in updating their estimates and, more generally, how sources influence each other. Furthermore, historical estimates can be compared in the same vein indicating how countries differ in their data quality. A first analysis in this direction is provided by Brockhaus and Kalkuhl (2014). However, as methods for some crops differ substantially, results are only a combined measure of data uncertainty and differences in methods. Future research should also explore how uncertainty about fundamentals is linked to prices, price volatility, and therefore potentially the behavior of traders, stockholders, and producers. Given the importance of information on supply and demand for both research and the functioning of agricultural markets, more research about the general accuracy of estimations would also be highly valuable. Considering the responsive supply found in chapter 6, the expected gains in price stability from timely information of higher quality can be substantial.

3 Emergency Reserves, Private Storage, or Trade? A Theoretical Analysis on Price Stabilization across Countries[9]

3.1 Abstract

Different governments around the world use trade and storage related policies to prevent high and volatile grain prices. Yet, investigations of these policies have either ignored private storage or not considered gains from international cooperation. This chapter compares the potential efficiency gains and fiscal costs of policies which aim to stabilize prices by controlling trade, subsidizing private storage, or setting up public emergency reserves in a two country setting. A partial equilibrium model with private stockholders and producers featuring rational expectations is used to capture dynamic interactions between agents. Contrary to existing works on private and public stockholding policies, this study compares gains from international cooperation and focuses on extreme events in addition to price volatility, both of which represent relevant political concerns. Findings illustrate the benefits from trade and that private storage, even if subsidized, hardly manages to avoid extreme price spikes despite being efficient in reducing price volatility. A (common) public emergency reserve behaves complementary. It is inefficient in reducing volatility but allows compensating large supply shortages at low fiscal costs while also showing fewer market distortions. Meanwhile, free trade is beneficial as long as countries are not too asymmetric in their characteristics and their trade policies are aligned. However, if only one country has a reserve, it needs to prevent leakages into foreign markets by imposing export restrictions when the reserve is used. Otherwise, this country alone will pay the costs to stabilize all countries thereby creating an international free-rider problem. If there are countries which use public stocks in combination with trade restrictions while others do not intervene into markets, prices in the latter group of countries can rise well above levels observed in the absence of any type of intervention. This can explain large price increases as observed in 2007/08. The high relevance of these findings for the ongoing WTO negotiations is discussed.

3.2 Introduction

Governments in developing countries around the world use different measures to protect their population from high and volatile food prices. The controversies around commonly used policies such as the maintenance of public buffer stocks, public emergency reserves, and trade

[9] Earlier versions of this work have been published in the conference proceedings of the 29th ICAE Conference 2015, Milan, as Brockhaus, J., Kalkuhl, M., “Grain emergency reserve cooperation – a theoretical analysis of benefits from a common emergency reserve” and in the proceedings of the ECOMOD conference 2015, Boston, as well as the GEWISOLA 2015, Gießen, (forthcoming as “Schriften der Gesellschaft für Wirtschafts- und Sozialwissenschaften des Landbaues e.V., Band 51, 2016) under the name “Emergency reserves, private storage, or trade? How to prevent extreme grain prices in a two country setting”.

restrictions, have been discussed in the general introduction, chapter 1. In short, buffer stocks have been heavily criticized for their high costs, low effectiveness, and market distortions impacting producers, speculators, and traders (Bigman and Reutlinger 1979; Gilbert 2011a; Glauber et al. 1989; World Bank 2005). However, the food price increases since the early 2000s have caused serious doubts on the underlying assumptions of these analyses. For example, it has been criticized that different important factors were underestimated such as the impact of high prices on poor people and magnitude to which markets are incomplete in many developing countries (Abbott 2010; Galtier 2013; Timmer 2010). This led to a new discussion about public food stocks, be they national or international, buffer stocks or emergency reserves, physical or virtual (Galtier 2014; HLPE 2011; von Braun and Torero 2009; von Braun et al. 2014). Export restrictions have been shown to allow stabilizing prices in one country (Anderson et al. 2013; World Bank 2010) while at the same time increasing world prices (Anderson et al. 2013; Headey 2010). India, for example, managed to limit the increase of domestic prices to 7.9% with the help of restricted exports while global prices increased by 160% from June 2007 to June 2008 (World Bank 2010). Researchers have thus repeatedly emphasized the need to limit trade restrictions (e.g. Bouët and Laborde Debucquet 2012; von Braun 2008). But as long as individual countries face incentives to impose restrictions and are not bound by international agreements, little progress can be expected in this area. As the WTO membership does not impose limits on export restrictions (Martin and Anderson 2011), it is thus not very surprising that more than 25 countries restricted exports in the years 2007 and 2008 (Demeke et al. 2009). Apart from increasing global prices, export restrictions are typically bad for domestic producers and traders whose profit margins are reduced. They may thus distort producer’s incentives (Anderson et al. 2010) and thereby amplify a potential crisis.

This study contributes to the discussion of how storage and trade policies may help to stabilize prices in different ways by addressing important questions in a theoretical framework incorporating public reserves, private storage, and trade in a two country setting. First, this study analyzes how restrictive trade policies impact the distribution of market prices. As there is only one homogeneous product, trade restrictions are imposed directly and no indirect restrictions such as quality standards exist (compare e.g. Heckelei and Swinnen 2012). Second, it illustrates how trade restrictions allow a single country to use a reserve for price stabilization while at the same time not having to fear leakages into foreign markets. Third, it shows how gains from cooperation can be achieved, i.e. how beneficial it can be for two countries to have a common reserve and keep trade unrestricted as long as the countries are not too asymmetric in terms of their domestic supply variability. Fourth, it illustrates how a public emergency reserve is very efficient in reducing the likelihood of extreme events while hardly impacting private market agents which is in huge contrast to a much more distorting private storage subsidy – a policy which used to be advocated within the “dominant doctrine”. However, such a subsidy allows reducing food price volatility while it remains an inefficient measure to tackle extreme events and thereby prevent price spikes. In brief, the private storage subsidy and the emergency reserve can therefore be seen as complementary policies. Finally, this study illustrates how these policies impact other market actors such as producers and arbitrage traders.

Based on the competitive storage model (Gustafson 1958; Newbery and Stiglitz 1982) which describes profit maximizing agents with rational expectations (Muth 1961), the model in this study incorporates private and public stockholding, spatial arbitrage, and consumers which are unable to self-insure themselves. This approach thereby follows the tradition of storage-trade models (Gouel 2011; Miranda and Glauber 1995; Williams and Wright 1991). While rational expectations have been criticized for inadequately modelling individual agents, they typically perform well in modelling the aggregated behavior of larger groups of agents and are supported by recent evidence on the competitive storage model (Cafiero et al. 2011; Peterson and Tomek 2005; compare also with chapter 3). The lack of opportunities for consumer self-insurance provides a rationale for government interventions (Innes 1990; Newbery and Stiglitz 1981). As buffer stocks have received numerous criticisms (compare section 1.1.6), this work instead focuses on a public emergency reserve. A buffer stock tries to keep prices within a predefined price band by selling or buying when prices are reaching the lower or upper threshold. This policy is often very costly, has historically failed in different circumstances (HLPE 2011), and is hard or impossible to defend against speculative attack (Salant 1983). Numerical analyses of buffer stocks are manifold (Gouel 2013b; Miranda and Glauber 1993; Miranda and Helmberger 1988; Wright and Williams 1988, 1982). In contrast, public emergency reserves do not try to protect consumers and producers at the same time but instead only focus on preventing very high prices (thereby automatically curbing price fluctuations). Most of the critique on buffer stocks does not apply to emergency reserves (compare section 1.1.6). For example, reserves focus on protecting consumers from extreme prices and thereby do not impose lower limits on prices. Therefore, fiscal costs of reserves are much smaller and more foreseeable than for buffer stock schemes. Second, as they remain untouched in normal times, they can better be combined with free trade. In this case, both stabilization mechanisms together can provide a much higher degree of price stability. Third, reserves are much less market distorting (compare results). Fourth, management rules for reserves are typically much simpler and therefore easier to anticipate by market actors thereby reducing market distortions. This also makes reserves less prone to be influenced by specific interest groups. Finally, emergency reserves can be shared between countries, even if the expected price distributions differ. This may reduce costs while at the same time increasing the level of price stability.

In normal times, a reserve remains untouched and full while releases only occur in times of substantial supply shortages. In this work, the emergency reserve is driven by a price peg policy, i.e. the minimum and maximum prices for buying and selling operations are the same. As long as market prices are below the pre-defined trigger price, the reserve remains full or is filled up to its (relatively low) capacity limit. Stocks are then released to prevent any price increase above the trigger price. This works until the reserve is fully replenished and only then, market price can increase above the trigger price. The reserve's capacity and trigger price should then be chosen such that the probability that the reserve is fully replenished is sufficiently low.

The advantages of following such a simple storage rule are manifold: It is easy to implement in practice by the managing authorities. Because its behavior can easily be anticipated by other market actors this results in minimal market distortions. Furthermore, violations of the stockholding rule can be easily observed which offers protection from misusage of the reserve. Otherwise, that is if storage rules are discrete or hard to observe, interest groups may lobby for specific interests or self-interested politicians may use stock releases to lower food prices before elections (Alesina and Gatti 1995; Sahley et al. 2005). Besides offering protection from misuse, such a reserve allows addressing most of other criticism buffer stocks have received. Stock levels and therefore fiscal costs can be easily controlled and kept at low levels. Furthermore, poor consumers are at the very heart of the intervention and no other groups may benefit at their cost. Additionally, market distortions through impacts on other market actors are very limited (compare with the results section and conclusions).

After price surges in recent years, many authors have investigated optimal food price stabilization policies in different settings: in a closed economy (Gouel 2013c), in a small open economy (Gouel and Jean 2015), in a poor grain importing country (Romero-Aguilar and Miranda 2014), or for a large country calibrated for wheat in India (Gouel et al. 2014). In a work which probably comes closest to this, reserves and private storage subsidies are compared for wheat in the Middle East (Larson et al. 2014). Storage cooperation scenarios have been explored to show costs and benefits (ECOWAS Commission 2012; Kornher and Kalkuhl 2015) and to illustrate the sustainability of a regional reserve with the possibility of default (Romero-Aguilar and Miranda 2015). However, these studies ignored the impacts on and interactions with private speculative storage and the supply response leading to results which may change if these restricting assumptions were relaxed. Without including private storage, different papers have analyzed the costs (and benefits) of (non-) cooperative trade policies (Bouët and Laborde Debucquet 2012; Gouel 2014b). In the context of the WTO trade negotiations, these policies have been discussed extensively (Bouët and Laborde 2010; Jean et al. 2010; Laborde and Martin 2012).

This study connects these three strings of literature: Optimal stabilization approaches which have previously been focused on one country, storage cooperation analyses which have suffered from very restrictive assumptions, and trade policy studies which have usually ignored the role of private speculative storage and a price-responsive supply. Thereby this study brings an important contribution to the question of how to implement storage policies in an open economy, a topic about which current knowledge is very limited (Gouel 2014a).

Furthermore, with very few exceptions (Gouel 2011; Larson et al. 2014), the role of extreme events has been largely ignored in the rational expectations storage literature. Nevertheless, extreme events are a very relevant political concern as they may cause a significant crisis, including riots, social unrest, and starvation. To tackle these issues, this work combines emergency reserves with private storage and supply response in a two country setting where both countries may have different trade or storage policies. Results shed light on the full price distribution, i.e. price volatility as well as the likelihood and severity of extreme events. Both of these matter for policy makers as volatile prices may reduce production and consumption (Banerjee and Duflo 2007; Binswanger and Rosenzweig 1986; Haile et al. 2014) whereas social unrest has been reported to be only caused by extreme prices (Bellemare 2015; Maystadt and Ecker 2014) or price increases (Arezki and Brückner 2011).

No attempt is made in this analysis to measure the welfare impacts of the different policies but instead only impacts on the distribution of prices, private stocks, public stocks, supply response, trade, and other response variables as well as fiscal costs for the government are compared. This is based on the shortcomings of welfare measures circulating in the literature. These assume linear or quadratic influences of prices and therefore do not account for the high welfare losses associated with extreme prices. Insufficient food intake, even if occurring only for a very limited amount of time, may have severe long-term impacts on the human body, in particular if food insecurity occurs during childhood (Chen and Zhou 2007; de Janvry et al. 2006). Thus, extreme prices which result in insufficient food intake and potentially lost lives cannot be captured within the framework of currently available welfare measures. Additionally, any such measure would inherently require subjective judgements for quantifying the value of a human live and the value of a healthy development of the brain and body. Furthermore, judgments about the distribution of welfare between consumers and producers would need to be made. As a result, this work refrains from making any such attempts but rather illustrates what can be objectively measured and then be used for making subjective judgements: the fiscal costs and the impacts of different policies on the prices and the behavior of agents considered in the model.

This chapter is structured as follows: Section 3.3 presents the theoretical model including the behavioral determinants of the different private market agents and the governments. Section 3.4 presents and justifies the calibration of the model. The results are depicted in section 3.5, grouped into subsections. First, the effects of trade policies are illustrated thereby highlighting how trade as a no-cost policy can help to stabilize prices. Yet, incentives to keep trade unrestricted vanish if one government alone decides to introduce price stabilization measures. Second, a private storage subsidy is shown to be efficient in reducing price volatility but not in tackling extreme events. Third, the influence of the reserve's capacity and trigger price on the price distribution and private stockholders are shown pointing out the limited impact of a well-designed reserve on private storage. Finally, it is revealed how high asymmetry, exemplarily illustrated by highly asymmetric production shocks, can hinder or even prevent international cooperation. Section 3.6 concludes.

3.3 Theoretical model

The model is an extension of the first trade-storage models which were developed (Miranda and Glauber 1995; Williams and Wright 1991). Its specification closely follows the approach developed by Christophe Gouel (Gouel and Jean 2015; Gouel 2011). However, it differs in several ways: (1) It explicitly includes two countries instead of one, (2) both of them have a public reserve following simplified rules as well as competitive private storage, (3) it includes flexible trade policies (e.g. by protecting the reserve), and (4) it has an explicit focus on extreme price events. These are the result of large supply shortfalls which arise if production, carry-over stocks, and imports combined are well below their expected level.

In the applied model, there are two countries, A and B, indexed by $i \in \{A, B\}$. If one country i is chosen, the other country is indexed as $-i = \{A, B\} \setminus \{i\}$. A homogeneous food product is produced, consumed, and stored in both countries and can be traded between them. This partial equilibrium dynamic programming model has annual time steps and combines trade, private stockholders, and public storage.

3.3.1 Private stockholders

One representative risk-neutral, profit maximizing stockholder exists in each country and acts competitively according to the competitive storage model (Gustafson 1958; Williams and Wright 1991). At time t the quantity $S_{i,t}$ is bought for price $P_{i,t}$ in country i and in time period $t+1$ this quantity is sold for price $P_{i,t+1}$. Storage losses δ_i and constant marginal storing costs k_i, which are considered to be equal in both countries, apply but may be (partly) compensated by the constant marginal storage subsidy m_i.[10] As a result, the stockholder's profit maximization problem can be expressed with the help of the rational expectations operator $E_t[.]$ as

$$V_i^S(S_{i,t-1}, P_{i,t}) = \max_{\{S_{i,t+j} \geq 0\}_{j=0}^{\infty}} E_t\left(\sum_{j=0}^{\infty} \beta_i^j \left[\delta_i P_{i,t+j} S_{i,t+j-1} - \left(P_{i,t+j} + k_i - m_i\right) S_{i,t+j}\right]\right), \quad (3.1)$$

where V_i^S is the stockholder's value function which includes the sum over all buying and selling operations and therefore depends on the stock levels, the market prices, the storage

[10] To be precise, one would need to consider different costs for placing into the stock, releasing from the stock, storing itself, and rotating the crop as well as for keeping the storage capacity. Furthermore, all these parameters would depend on the actual stock levels. However, this would massively increase the complexity while providing very limited additional insights. Therefore, only constant marginal storage costs, which are assumed to cover all these processes, were considered.

costs and the storage subsidy. The index for the time periods is j, so the maximization problem is solved for all time periods simultaneously. There are two discount factors in this equation, $\beta_i = 1/(1 + r_i)$ (with r_i representing the interest rate) is the monetary discount factor whereas δ_i represents the discount factor originating from the storage losses. Representing this equation in a recursive form allows rewriting the problem as the following Bellman equation:

$$V_i^S(S_{i,t-1}, P_{i,t}) = \max_{S_{i,t}\geq 0}\left(\delta_i P_{i,t} S_{i,t-1} - (P_{i,t} + k_i - m_i) S_{i,t} + \beta_i E_t\left[V_i^S(S_{i,t}, P_{i,t+1})\right]\right) \tag{3.2}$$

This equation can be rewritten as a complementarity problem using the first-order condition on the stocks, the envelope theorem, and the non-negativity constraint on the stocks (Gouel 2011). The resulting complementarity problem reads as

$$S_{i,t} \geq 0 \perp P_{i,t} + k_i - m_i - \delta_i \beta_i E_t(P_{i,t+1}) \geq 0 \ . \tag{3.3}$$

Here, the $\perp$ symbol represents the orthogonality of the mixed complementarity problem. In general, a mixed complementarity problem $x^{min} \leq x \leq x^{max} \perp F(x)$ consists of a continuously differentiable function $F: \mathbb{R}^n \rightarrow \mathbb{R}^n$ and $x^{min} \in (\mathbb{R} \cup -\infty)^n, x^{max} \in (\mathbb{R} \cup +\infty)^n$ as lower and upper bounds, respectively, such that for each $i \in \{1, \dots, n\}$ one out of the following conditions holds:

$$F_i(x) = 0 \text{ and } x_i^{min} \leq x_i \leq x_i^{max} \quad \text{or} \tag{3.4}$$

$$F_i(x) > 0 \text{ and } x_i^{min} = x_i \quad \text{or} \tag{3.5}$$

$$F_i(x) < 0 \text{ and } x_i = x_i^{max} \quad . \tag{3.6}$$

If $x^{max} = \infty$ (or $x^{min} = -\infty$), then $F(x) \geq 0$ (≤ 0) $\forall x$, as it is the case for the private storage problem above. If $x^{max} = \infty$ and $x^{min} = -\infty$, then $F(x) = 0$ is a “traditional” equation.

3.3.2 Public emergency reserve

Both countries have a public emergency reserve. These follow simple rules which make the results more understandable and transferable to real-world situations. Only two parameters are used to operate the reserve, its capacity, c_i, and its trigger price, T_i. As long as the observed price is below the trigger price, the reserve is filled up to its capacity whereas stocks are released to prevent any price increase above the trigger price until the reserve is depleted. Only then, market price can increase above the trigger price. This behavior can be expressed as the following complementarity problem:

$$P_{i,t} - T_i \perp 0 \leq R_{i,t} \leq c_i \tag{3.7}$$

where $R_{i,t}$ represents the level to which the reserve in i is filled at time t. If both countries have a reserve and trade is free, it is called reserve cooperation because they share the costs but also the benefits from their public reserves. In contrast, if only one country has a reserve, depending on the trade policy the benefits may be shared while the costs never are.

3.3.3 Production

Planting decisions in i depend on the price expectations about the future prices at $t+1$ in time period t with the knowledge available then. Therefore, the representative and risk-neutral producer in each country makes his planting decision $H_{i,t}$ at time period t while the crop is only harvested one period later. Additionally, there are random, normally distributed yield shocks $e_{i,t}$ with mean 1 and variance σ_i so that the final production can be written as $H_{i,t}e_{i,t+1}$. This assumption is justified by the weak evidence against normally distributed harvest shocks (Just and Wenninger 1999). In theory, production could become negative under the assumption of normally distributed production shocks. But the values chosen for the calibration ensure that production levels stay in the expected ranges and will under no reasonable level of simulated time periods ever become negative. The resulting profit-maximizing production decision of the producers then reads as

$$\max_{\{H_{i,t+j}\geq 0\}_{j=0}^{\infty}} E_t\left(\sum_{j=0}^{\infty} \beta_i^j \left[\delta_i P_{i,t+j} H_{i,t+j-1} e_{i,t+j} - \Psi_i\left(H_{i,t+j}\right)\right]\right). \tag{3.8}$$

Here, $\Psi_i\left(H_{i,t+j}\right)$ represents the production costs for producing $H_{i,t}$. As before, this problem can be rewritten in recursive form providing

$$\beta_i E_t\left(P_{i,t+1} e_{i,t+1}\right) = \Psi_i'\left(H_{i,t}\right) \tag{3.9}$$

This equation can be interpreted as follows: The marginal cost of production is equal to the expected, discounted marginal profit from one unit of planned production. Following economic theory, the first derivative of the production cost function needs to be strictly increasing which can be fulfilled by choosing a convex, isoelastic function of the form

$$\Psi_i\left(H_{i,t}\right) = h_i \frac{H_{i,t}^{1+\mu_i}}{1+\mu_i} \tag{3.10}$$

with scale parameter h_i and $\mu_i \geq 0$ as the inverse supply elasticity. Hence, this specification was chosen for the model.

3.3.4 Trade

All possibilities for spatial arbitrage are used by the representative trader who is trading competitively between the two countries. Trade is instantaneous with per unit trading costs of Θ_i for exports from i to $-i$, i.e. the other country. In addition, a country may impose an export tariff $\phi_{i,t}$. As trade happens instantaneously, instant profits rather than expected profits are maximized. Expressed as a complementarity problem, the trader's behavior can be described as

$$P_{i,t} - P_{-i,t} + \Theta_i + \phi_{i,t} \perp 0 \leq X_{i,t} \leq X_i^{max} \tag{3.11}$$

Here, $P_{-i,t}$ is the price at t in the country which is not i, and $X_{i,t}$ are the exports from country i to the other country. A direct result from this equation is that there are never simultaneously exports to and imports from the same country, i.e. $X_{i,t} \geq 0 \perp X_{-i,t} \geq 0$. Governments may set a quota, i.e. a limit to the maximum allowed amount traded which is represented by X_i^{max}. Furthermore, governments may decide that exports are allowed only as long as their reserve remains untouched. For the numerical implementation, this case can be represented by adjusting the export tariff whenever the reserve is used. The following complementarity condition describes this behavior

$$T_i - P_{i,t} + R_{i,t} - c_i \perp 0 \leq \phi_{i,t} \leq \phi_i^{max} \tag{3.12}$$

where ϕ_i^{max} describes the maximum export tariff which could be infinity. This equation sets $\phi_{i,t} = 0$ as long as the price is below the trigger ($T_i > P_{i,t}$; which implies that the reserve is filled completely, so $R_{i,t} = c_i$); it sets $\phi_{i,t}$ = ϕ_i^{max} if the reserve is not filled up to its capacity ($R_{i,t} < c_i$, implying $T_i < P_{i,t}$), and in the remaining cases this equation adjusts $\phi_{i,t}$ such that exports do occur but only precisely up to the point where the reserve would be touched.

3.3.5 Consumption

The consumers in both countries have an isoelastic consumption function

$$D_i(P_{i,t}) = \gamma_i P_{i,t}^{\alpha_i} \tag{3.13}$$

where γ_i is a normalization parameter and $-1 \neq \alpha_i < 0$ is the price elasticity. This implies that consumers have a constant income and do not save and, as a result, do not insure themselves. If they did, there would be another maximization problem for the consumer which needed to be solved and this would go beyond the scope of this analysis.

3.3.6 Fiscal costs

Fiscal costs only arise if a government intervenes into a market which can be done by paying a subsidy to private stockholders, by maintaining a public emergency reserve, or by limiting trade. For a constant marginal private storage subsidy m_i, the storage costs k_i are shared between the government who pays m_i and the private stockholder who pays $k_i - m_i$. The subsidy m_i has an upper bound, $m_i \leq k_i + \bar{P}_i(1 - \delta_i\beta_i)$, because otherwise storage would always become profitable and therefore stock levels would diverge. However, there may also be a tax ($m_i < 0$) on storage resulting in $k_i - m_i > k_i$ and therefore very low private stock levels. For any level of private subsidy, the fiscal costs within one period can be calculated as $S_{i,t}m_i$ resulting in fiscal costs for all periods $t = 1 \dots n$ of

$$\sum_{t=1}^{n} S_{i,t} m_i \beta_i^n \ . \tag{3.14}$$

The total fiscal costs for all periods depend on the number of periods. It is therefore preferable to use the expected per-period costs for comparing different scenarios. These can also be calculated from the simulation results as

$$\frac{1}{n}\sum_{t=1}^{n} S_{i,t} m_i \ . \tag{3.15}$$

These expected per-period costs do not depend on the discount factor. When comparing different scenarios, it turns out that the relative value of both cost measures is the same if the number of simulated periods (shock realizations) is high enough. This is due to the random shock realizations because the discount factor would affect all production levels in the same way and as a result not change the relative importance of individual realizations. Owing to the superior comparability, only the expected per-period costs are calculated for the subsequent factors which contribute to the total fiscal costs.

For a public emergency reserve, the government has to pay the full storage costs which are assumed to be equal to the gross marginal storage costs k_i for private stockholders. Therefore, the fiscal costs for storing the amount in the reserve is $R_{i,t}k_i$ for any specific period. In addition, fiscal costs arise as the reserve is filled up when prices are below the trigger price. In contrast, stock releases take place when market prices reach or surpass the trigger price until the reserve is replenished completely. This produces revenues of $(R_{i,t} - R_{i,t-1})P_{i,t}$. As a result, the expected per-period fiscal costs for the reserve are

$$\frac{1}{n}\sum_{t=1}^{n} \left[R_{i,t}k_i - \left(R_{i,t} - R_{i,t-1}\right)P_{i,t}\right] \ . \tag{3.16}$$

If trade is limited by a variable export tariff $\phi_{i,t}$, the government can collect fiscal revenues from exports. Even if trade is not limited by a variable export tariff but by a fixed quota which dictates the maximum level of exports, the government can still collect the profits from the traders, e.g. by selling the quota in auctions. In both cases, the expected per-period revenues can be calculated as

$$\frac{1}{n}\sum_{t=1}^{n} \left(P_{-i,t} - P_{i,t} - \Theta_i\right)X_{i,t} \ . \tag{3.17}$$

All the fiscal costs and revenues are summed up. For achieving a more intuitive interpretation, they can be expressed as share of the agricultural GDP. However, as the agricultural GDP may change between different scenarios, this could make the relative costs incomparable. But it turns out that the expected agricultural (production) GDP

$$\frac{1}{n}\sum_{t=1}^{n}\left(P_{i,t}H_{i,t}e_{i,t}\right)\approx 1 \tag{3.18}$$

is sufficiently close to 1 in all scenarios[11]. Hence, the fiscal costs can still be interpreted as a share of the agricultural GDP without being divided by the latter. But even if they are divided, this does not change any results.

3.3.7 Market equilibrium

To limit the number of state variables, the private carry-over stocks, the emergency reserve, and the harvest can be combined to one state variable per country, availability $A_{i,t}$, which results in the following transition equation

$$A_{i,t} = (1-\delta_i)\left(S_{i,t-1}+R_{i,t-1}\right)+H_{i,t-1}e_{i,t} \tag{3.19}$$

As the shocks are considered at the beginning of each period, the knowledge of the availability in both countries fully determines the state of the model. Then, the market equilibrium condition reads as

$$A_{i,t}-X_{i,t}+X_{-i,t} = D_{i,t}\left(P_{i,t}\right)+S_{i,t}+R_{i,t} \tag{3.20}$$

When the model is solved, a recursive equilibrium is calculated by evaluating how the response variables change dependent on the state variables. This means the following functions are calculated by using the aforementioned behavioral equations for the different agents: $S_{i,t}\left(A_{i,t},A_{-i,t}\right), R_{i,t}\left(A_{i,t},A_{-i,t}\right), H_{i,t}\left(A_{i,t},A_{-i,t}\right), X_{i,t}\left(A_{i,t},A_{-i,t}\right), \phi_{i,t}\left(A_{i,t},A_{-i,t}\right)$, and $P_{i,t}\left(A_{i,t},A_{-i,t}\right)$.

For simplicity, it is assumed that storage costs are the same in both countries and storage losses are zero. Changing this assumption does slightly affect the specific result but it does not influence the general behavior of the model and therefore the conclusions remain valid even if these assumptions were relaxed.

3.4 Calibration

The default values for solving the rational expectations mixed complementarity problem and simulating the scenarios are illustrated in Table 3.1. For each configuration, i.e. each set of parameters, the model is solved on a 50x50 grid of the state variables. This selection is justified and explained in the appendix (chapter 8.1). Typical values, which were found in the literature and in other models, were used for all parameters and explanations are provided in

[11] $H_{i,t}e_{i,t}$ is the production level (planned production multiplied by shock) multiplied by prices. Thus, this yields the agricultural GDP.

the table. However, these values are theoretical values which only have a relative interpretation as the model is not calibrated for two specific countries. In most scenarios, trade was not restricted. For the reserve, the characteristics of the response variables have been calculated for a reserve size between 0.5% and 10% of the mean harvest and trigger prices from 1.1 to 1.6 (with the expected price being more or less equal to one). For private storage, different subsidies have been considered ranging from zero effective storage costs to a per-period storage tax of 0.04. The other simulated scenarios are summarized in Table 3.1. The models are solved and simulated in MATLAB using the RECS solver (Gouel 2013a) and the CompEcon toolbox (Miranda and Fackler 2011).

3.5 Results

The presented model has been solved and simulated for different settings. At first, some distinct scenarios are modelled to illustrate the effects of trade policies and asymmetric trade policies. Second, the influence of the reserve characteristics is modelled. Third, reserve policies are compared with private storage policies and finally illustrations about countries with asymmetric characteristics follow.

3.5.1 Trade policies and asymmetric reserve policies

To illustrate the general effects of having a reserve, allowing trade, using different trade policies and having asymmetric reserve policies, eight different scenarios are modelled (Table 3.2). Scenario 1, no trade and no reserve, is unrealistic but an important illustrative scenario to provide a baseline to compare policies with. Scenario 2, free trade without a reserve, is the liberal free market case without any government intervention. Scenario 3, no trade but a reserve, is the autarky case which is still targeted by some countries. The case where one country uses government interventions to stabilize prices in an open world with free trade is depicted in scenario 4. This case is useful to highlight the problems associated with price stabilization in an open economy. Scenario 5 uses trade restrictions to prevent the leakage of benefits into foreign markets. Scenario 6 shows the same situation with the difference that only some countries have public reserves. This situation is similar to the behavior of many governments during the world food crisis in 2007/08 and can be used to explain corresponding price spikes. Scenario 7 is used to illustrate the effects of price quotas. Eventually, scenario 8 shows the case of storage-trade cooperation.

Table 3.1: The default values for the simulations.

Parameter	Symbol	Default value	Comments / Explanation of choice
Reserve price trigger in A	T_A	1.3	Based on results about price stability
Reserve price trigger in B	T_B	1.3	Based on results about price stability
Reserve capacity in A	c_A	0.02	Calibrated for reasonable fiscal costs[1]
Reserve capacity in B	c_B	0.02	Calibrated for reasonable fiscal costs[1]
Mean supply in A	$\tilde{\sigma}_A$	1	(Only relative value matters)
Mean supply in B	$\tilde{\sigma}_B$	1	(Only relative value matters)
SD of supply shock in A	σ_A	0.06	See section 4.4
SD of supply shock in B	σ_B	0.06	See section 4.4
SD of sup. shock correl. A to B	σ_{AB}	0	For illustrating max. coop. gains
SD of sup. shock correl. B to A	σ_{BA}	0	For illustrating max. coop. gains
Marginal storage costs in A	k_A	0.06	Common value for such models
Marginal storage costs in B	k_B	0.06	Common value for such models
Supply elasticity in A	μ_A	0.2	Gouel, Gautam & Martin (2014)
Supply elasticity in B	μ_B	0.2	Gouel, Gautam & Martin (2014)
(Demand) Price elasticity in A	α_A	-0.2	Typical for FAPRI and USDA data
(Demand) Price elasticity in B	α_B	-0.2	Typical for FAPRI and USDA data
Real interest rate in A	r_A	0.03	Common value for such models
Real interest rate in B	r_B	0.03	Common value for such models
Trade costs from A to B	Θ_A	0.05	Based on comparison to storage costs
Trade costs from B to A	Θ_B	0.05	Based on comparison to storage costs
Relative country size of A	γ_A	1	(Only relative value matters)
Relative country size of B	γ_B	1	(Only relative value matters)
Maximum exports from A to B	X_A^{max}	100,000	For unrestricted trade
Maximum exports from B to A	X_B^{max}	100,000	For unrestricted trade
Maximum export tariff A to B	ϕ_A^{max}	0	For unrestricted trade
Maximum export tariff B to A	ϕ_B^{max}	0	For unrestricted trade
Parameters for	solving	and simulating	
Grid points	-	50x50	High precision
Min. grid point	-	0.6x0.6	Solid lower bound
Max. grid point	-	1.7x1.7	Solid upper bound
Grid density	-	0.022	High precision
MCP Solver	-	Path	High precision
Shock nodes	-	7	High precision
Solving method for RE equilibrium	-	Successive approximation	Computational speed
Function approximation method	-	Response variables	Computational speed
Simulations: Shock realizations	-	600x200	High precision
Simulation method between grid points		Solve	High precision

Notes: Own illustration. Unless specified differently, the above specifications were used for simulating the model.

[1] Calibration of the capacity and trigger based on results from section 3.5.3.

Table 3.2: Overview of scenarios which were simulated (Own illustration)

Scenario	Description	Variables differing from default
1	No trade, no reserve	$\Theta_A = \Theta_B = \infty; c_A = c_B = 0$
2	No reserve	$c_A = c_B = 0$
3	No trade	$\Theta_A = \Theta_B = \infty$
4	Reserve only in country A	$c_B = 0$
5	Trade only if reserves are untouched	$\phi_A = \phi_B = \infty$
6	Scenario 4 and 5 combined	$c_B = 0$, $\phi_A = \infty$
7	Trade only up to capacity of reserve	$X_A^{max} = X_B^{max} = c_A = c_B$
8	Common reserve	

The statistical properties of the price distributions (Figure 3.1, Table 3.3), the reserve[12] and availability distributions (Table 3.4) and distributions of private storage, production, and exports (Table 3.5) build the foundation of the subsequent discussion. Unless the country is shown in brackets behind the scenario, statistical properties are symmetric between both countries. Percentiles or quantiles can also be interpreted as events which are expected to happen every corresponding couple of years. As an example, the price at the 90th percentile can be interpreted as a price which is expected to roughly occur every 10 years; or one could say that only once in ten years the price is expected to be at around such a high level. As the expected prices are around 1, a price of say 1.2 can be interpreted as around 20% above the expected price. Other variables can be interpreted accordingly.

In **scenario 1**, no trade and no reserve, a huge price range, in particular on the upper end, is observed and comes with relatively high mean prices and a high standard deviation, skewness, and kurtosis (Figure 3.1, Table 3.3). In extreme events, prices may double or more. The mean private stock levels are relatively large and supply response is the strongest along with no-trade-scenario 3 which is indicated by the high standard deviation (Table 3.5).

Scenario 2, in which there is no reserve, illustrates that trade is a no-cost policy which is very effective in preventing high prices for symmetric countries. Trade manages to reduce all moments of the prices and massively decreases the highest percentiles of the prices (Figure 3.1, Table 3.3). However, trade also strongly reduces private stocks and the supply response in all parts of the distribution (Table 3.5). The mean private stocks are almost halved (the difference in the mean private stocks can be regarded as a crowding out factor). Once trade is allowed, it is hardly affected by the different scenarios except if trade is only allowed when the reserve remains untouched, if it is limited by the capacity of the reserve, or if there is a large private storage subsidy (not shown but available upon request).

[12] To avoid rounding problems, a maximum relative deviation of 0.1% was allowed for frequencies above zero, and a maximum absolute deviation of 0.0001 for frequencies of zero (e.g. no trade).

The effects of having an emergency reserve but no trade are depicted in **scenario 3**. All moments of the price distribution and the prices of the higher percentiles are decreased substantially. The reserve does not affect the minimum prices and hardly affects the prices below the mean because it is usually filled up to its capacity. When compared to introducing trade, the reserve seems less attractive though: Trade reduces the prices of the highest percentiles even more and does not produce any fiscal costs which clearly underlines the benefits from trade. However, the extent to which the highest percentiles of prices are reduced depends on the reserve's capacity and trigger price. In contrast to allowing trade, private storage is hardly influenced by the introduction of a reserve. Hence, such a reserve presents itself as a stabilization tool which shows hardly any market distortions. In this scenario, the frequency of the reserve being empty or non-full is the highest. While the reserve only affects the highest percentiles of the supply response, trade mostly affects the lowest percentiles (not shown in the tables).

Table 3.3: Price characteristics for the simulation of the different scenarios

Scenario	Prices										Costs
	Mean	SD	Skew	Kurt	1%	50%	90%	95%	99%	99.9%	(in %)
1	1.016	0.222	2.56	13.1	0.78	0.94	1.3	1.47	1.86	2.48	0
2	1.009	0.162	1.82	7.6	0.81	0.96	1.23	1.34	1.57	1.9	0
3	1.016	0.201	2.12	10.9	0.78	0.94	1.3	1.37	1.72	2.3	0.041
4 (A)	1.009	0.153	1.51	6.1	0.81	0.96	1.24	1.3	1.5	1.81	0.074
4 (B)	1.009	0.154	1.55	6.2	0.81	0.96	1.24	1.33	1.51	1.82	0
5	1.01	0.156	1.96	11.7	0.81	0.96	1.25	1.3	1.5	2.03	0.08
6 (A)	1.006	0.147	1.35	5.3	0.81	0.96	1.24	1.3	1.44	1.75	0.079
6 (B)	1.013	0.174	2.56	15.3	0.81	0.95	1.24	1.32	1.67	2.25	0
7	1.01	0.174	1.89	9.5	0.8	0.94	1.28	1.3	1.59	2.08	-0.019
8	1.009	0.148	1.28	4.9	0.81	0.96	1.25	1.3	1.43	1.73	0.082

Notes: Own illustration. Different countries are indicated in brackets for asymmetric scenarios. The columns show the mean, standard deviation, skewness, kurtosis, and different percentiles of prices for the respective scenario. Fiscal costs are depicted in the last column. The scenarios refer to: (1) no trade, no reserve, (2) no reserve, (3) no trade, (4) reserve only in A, (5) trade only if reserve full, (6) combination of 4 and 5, (7) trade quota, (8) common reserve.

Only one country (A) has a reserve in **scenario 4**, but both countries benefit from it to almost the same extent (compare rows 4(A) and 4(B) in Table 3.3). The mean, SD, skewness, and kurtosis are all reduced and there is a huge decline of the prices in the higher percentiles. The benefits are almost completely shared, i.e. the benefits largely "leak" into the other country, so that one country is paying the cost to stabilize both of them while almost having no benefits over the other country as prices in the highest percentiles only differ by costs of trade. Yet, the effects of one reserve alone are already very significant as the standard deviation and the prices of the highest percentiles (when the reserve is touched) are much lower than in the scenarios without trade or without reserve. Private storage in either country remains basically unaffected from the reserve when compared to scenario 2. Due to trade as second stabilization mechanism, the reserve remains more filled than in scenario 3 without trade. The supply response is comparable to the scenario without trade and exports hardly change compared to the scenario 2 without reserve. Since the benefits from the reserve are largely shared, this scenario also shows that it is possible to share a reserve which is – for logistical or other reasons – located in one country only while the costs are shared.

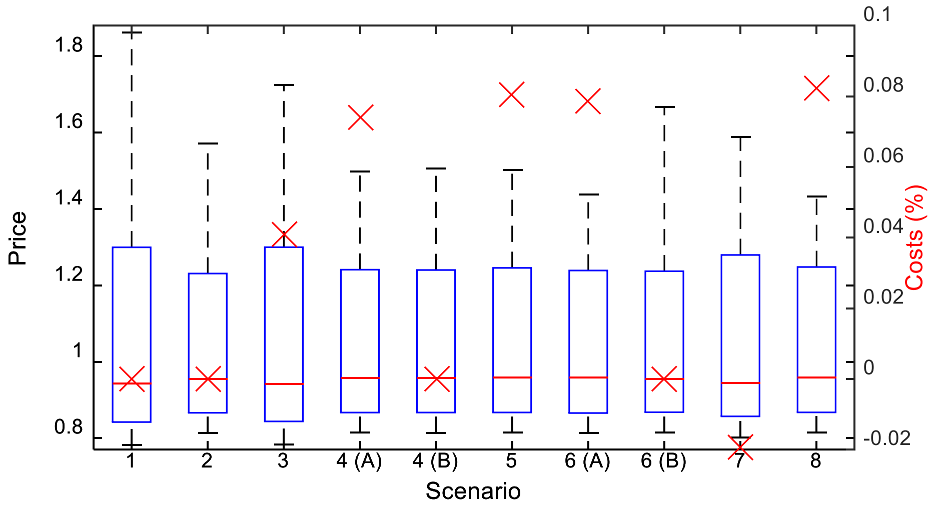

Figure 3.1: Price characteristics and fiscal costs of different scenarios

Notes: Own illustration. For the simulated scenarios the box-plots show the 1st, 10th, 50th, 90th, and 99th percentile of the price distribution (left axis). The crosses illustrate the fiscal costs expressed in % of agricultural GDP which are shown on the right axis. Price interpretation: As the expected price is close to 1 in all scenarios, a price of 1.2 can be interpreted as 20% above the expected price.

In **scenario 5**, trade only occurs whenever the reserves remain untouched which leads to the lowest frequency of an empty or non-full reserve. While the frequency of exports is slightly reduced compared to the aforementioned scenarios with trade, private storage remains unchanged. Compared to scenario 4 with only one reserve in both countries (or to the common reserve), the 99th percentile slightly decreases while the 99.9th percentile increases. This illustrates the mechanism of such a restrictive trade policy: Prices in "normal times" are slightly more stable due to the anticipated prevention of letting the other country induce a crisis. However, while prices are protected from external shocks, they are more prone to rise from internal shocks as the external stabilization mechanism is missing. Furthermore, prices during extreme events in both countries are higher in the country which is more affected because of the lack of cooperation – i.e. sharing of the burden of high prices – in this case. In addition, now both countries have a reserve and therefore both need to pay the fiscal costs. For the same fiscal costs but with unlimited trade, the highest percentiles (99.9th and above) of the prices can be reduced significantly as can be seen in scenario 8, the common reserve.

If one country wants to set up a reserve while at the same time preventing this reserve from leaking into the other country, it can use the trade policy of scenario 5. This configuration is the basis of **scenario 6**, where only country A has a reserve. While in this case, country A has to pay all the costs for the reserve, it also manages to reduce the highest percentiles much more than if trade were allowed in times of supply shortages (scenario 4). Hence, if one country alone were to set up a reserve, this kind of policy could be used to prevent leakages to foreign countries (assuming that trading partners do not use retaliation measures). Scenario 6 therefore comes close to the behavior of many governments during the world food crisis in 2007/08, which introduced export bans when prices spiked. Indeed, the probability of price spikes or extreme events is higher than in all other scenarios that do not totally forbid trade. Prices in country B can be enormous and this can explain the dramatic increase of global prices in 2007/08. In order to prevent extreme events, it would be better for country B if country A would abandon its reserve but therefore keep its borders open (scenario 2) or at least only impose trade quotas (scenario 7).

Table 3.4: Availability, reserve characteristics and fiscal costs

	Availability		Reserve				Costs
	Mean	SD	Mean	SD	Freq(empty)	Freq(nun-full)	(in %)
1	1.03	0.064	0	0	1	1	0
2	1.016	0.063	0	0	1	1	0
3	1.045	0.064	0.018	0.005	0.069	0.118	0.041
4 (A)	1.034	0.063	0.019	0.004	0.044	0.069	0.074
4 (B)	1.015	0.063	0	0	1	1	0
5	1.034	0.063	0.019	0.004	0.03	0.053	0.08
6 (A)	1.033	0.063	0.019	0.004	0.029	0.051	0.079
6 (B)	1.017	0.063	0	0	1	1	0
7	1.039	0.063	0.019	0.005	0.052	0.091	-0.019
8	1.034	0.063	0.019	0.004	0.038	0.063	0.082

Notes: Own illustration. Different countries are indicated in brackets for asymmetric scenarios. For the reserve, the frequencies of it being empty and non-full are shown as well as the costs in percent of the agricultural GDP.

Scenario 7 illustrates the effect of a trade quota as trade is limited by the capacity of the reserve. The frequency of trade is the highest in this scenario while the amounts traded are among the lowest. This implies that trade is only partly instantaneous and partly delayed by one or more years, depending on the trading limit and supply shock. However, the trade quota generates revenues which significantly reduce the fiscal costs of this policy. The frequency of having an empty or non-full reserve is the highest among all scenarios with trade. Compared to scenario 8 where trade is unlimited, there is only a slight increase in private stocks such that private storage cannot compensate for the damaging effect of such a trade quota. Interestingly, the mean price, the standard deviation and the highest percentiles are all higher than in scenario 5 or 8. Therefore, limiting the per-period amount of trade seems to have a more devastating impact on the price stability than limiting trade to periods where the reserve remains untouched. As a result, if only one country builds up a reserve and wants to protect itself from paying the costs to stabilize prices in the other country, a trade policy based on whether the reserve is touched is a better option than introducing time-independent quotas. However, governments usually do not impose time-independent quotas. Instead, they are introduced in times of crisis such as in 2007/08 when Ukraine and other countries (AMIS 2011b) introduced export quotas. In that case, the quotas could be applied to prevent leakages from public stocks into foreign markets which would make them comparable to an export tariff.

Table 3.5: Private storage, production, and export characteristics

	Private storage				Production		Exports			
	Mean	SD	50%	90%	Mean	SD	Mean	SD	90%	Freq(trade)
1	0.029	0.033	0.018	0.078	1.001	0.011	0	0	0	0
2	0.015	0.026	0	0.055	1.001	0.007	0.011	0.021	0.042	0.336
3	0.026	0.032	0.012	0.073	1	0.01	0	0	0	0
4 (A)	0.014	0.026	0	0.053	1	0.007	0.011	0.021	0.042	0.34
4 (B)	0.015	0.026	0	0.053	1	0.007	0.011	0.021	0.042	0.341
5	0.014	0.026	0	0.052	1	0.007	0.011	0.021	0.041	0.333
6 (A)	0.014	0.026	0	0.052	1	0.007	0.01	0.02	0.04	0.321
6 (B)	0.015	0.026	0	0.055	1.001	0.008	0.011	0.021	0.043	0.346
7	0.019	0.026	0.005	0.058	1.001	0.009	0.006	0.009	0.02	0.37
8	0.014	0.025	0	0.052	1	0.007	0.011	0.021	0.042	0.341

Notes: Own illustration. Different countries are indicated in brackets for asymmetric scenarios. The frequency of exports being larger than zero is shown in the last column.

Scenario 8, the common reserve (or two identical reserves and unlimited free trade) allows the biggest reduction of the highest percentiles of prices; the price in the 99.9th percentile is by far the lowest. Therefore, such a common reserve is the best mechanism to compensate extreme supply shortfalls. Interestingly, for smaller supply shortfalls prices can be reduced slightly more if trade is limited to times when the reserve is untouched. This might be a result of the decrease in private stocks (in particular in the highest percentiles) if trade is not limited[13], it might be due to the slight reduction in trade which produces fewer trade costs, or it could be due to the protection from external shocks. The reserve is used less frequently than if trade is restricted whenever the reserve is touched (scenarios 5 and 6), but it is slightly more often replenished as these trade restrictions limit the influence of external shocks. However, the trade quota leads to a higher frequency of an exhausted reserve. Compared to the other scenarios where trade is allowed, private storage remains almost unaffected. Overall, the reserve is only touched in around 20% of the cases and is replenished with a probability of

[13] This leads to lower prices as the trade costs are included in the prices.

around 3.5%. These results illustrate that such a common reserve provides a good protection against extreme production shortfalls at very little costs (around 0.08% of the agricultural GDP).

3.5.2 Private storage subsidy

After having illustrated the effects of trade policies and asymmetric reserve policies, the impact of a common private storage subsidy in two symmetric countries with free trade is presented in this section. Both countries have the same subsidy m_i which reduces the effective per-unit storage costs to $k_i - m_i$. Figure 3.2 shows how these costs influence different percentiles of the prices (left axis) and which fiscal costs they produce for the government (right axis). High subsidies significantly reduce the highest percentiles of the prices. However, this exponential decrease is accompanied by an exponential increase in fiscal costs reaching as high as 0.26% of the agricultural GDP when private storage is effectively free. In addition, the prices of the lower percentiles (the 25th percentile is indicated in cyan) increase, so the standard deviation is reduced because prices from both ends of the distribution are shifted toward the mean. In general, only when the supply is relatively high, private storage occurs at all. This prevents private storage from compensating supply shortages, particularly if several of these occur in a row. Trade is heavily reduced by the storage subsidy. More precisely, the frequency, the mean exports, and the higher percentiles are reduced (not shown). Policymakers therefore need to be aware of these large impacts of a storage subsidy on trade. Section 3.5.4 compares the cost-effectiveness of a private storage subsidy to a public emergency reserve.

3.5.3 Influence of the reserve parameters on a common reserve

For the public emergency reserve, there are two parameters which can be varied by policymakers, the capacity and the trigger price. This section looks at the effect of these parameters on prices and costs while assuming that both countries cooperate by following the same reserve policies and keeping trade free. Figure 3.3 shows the 99.9th percentile, the 99th percentile, the 90th percentile, the fiscal costs, and the frequency of an empty or non-full reserve as colors in separate plots with the reserve capacity on the x-axis and the trigger price on the y-axis. This shows how these variables change if the reserve capacity and/or the trigger price are changed. The percentiles can again be interpreted as a shock of a certain frequency, i.e. the 99th percentile is a 100-year shock, the 90th percentile a shock which is expected to occur roughly every 10 years. In the graphs with the different price percentiles it can be seen that if the trigger price is very low, the reserve might not be able to keep the price of the respective percentile below it. If the reserve is supposed to affect prices at the 90th percentile already, it is necessary to set the trigger price below 1.3. But these low trigger prices are likely to fail in compensating large supply shortages unless they come with a big reserve and therefore high fiscal costs. As a numerical example, a reserve capacity of 0.025, i.e. 2.5% of the average harvest, combined with a trigger price of 1.2, i.e. 20% above the average price, would allow keeping the 90th percentile below the trigger price while the 99th percentile equals 1.4 and the costs of this policy would be around 0.077% of the agricultural GDP.

A common concern with public stockholding is the crowding out of private storage (see chapter 5). This crowding out effect is calculated for the different reserve configurations (Figure 3.4). The private stocks at the 99.9th percentile, the 99th and the 90th percentile, and, most importantly, the mean private stocks are shown. Obviously, any reserve which is supposed to impact the price distribution will also impact private storage. However, it can be seen that if the reserve's capacity is not too high and the trigger price is not too low, the impact of the reserve on private storage can be minimal. In the numerical example above with a reserve capacity of 0.025 and a trigger price of 1.2, the mean private stocks would be reduced from roughly 1.5% to 1.24% of the production. A price trigger of 1.275 would already prevent the mean private stocks from going below 1.3% of the production, independent of the capacity. Overall, the impact on private storage seems to be small compared to the other scenarios before. Prohibiting or limiting trade for example has a much bigger impact on private storage.

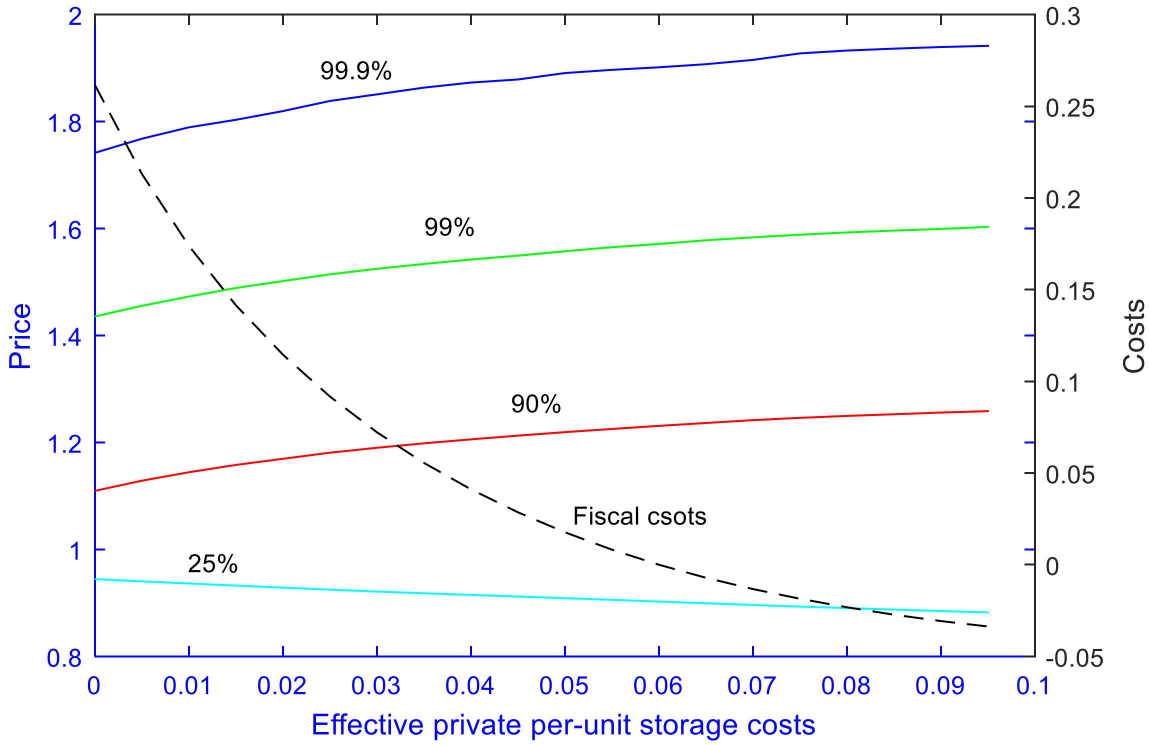

Figure 3.2: Price distribution for the storage subsidy

Notes: Own illustration. Percentiles (lines) are indicated on the left y-axis whereas fiscal costs expressed as % of agricultural GDP (dashed black) are depicted on the right y-axis. As the default per-unit private storage costs are calibrated to 0.06, higher values on the x-axis represent a storage tax which brings revenues, i.e. negative fiscal costs.

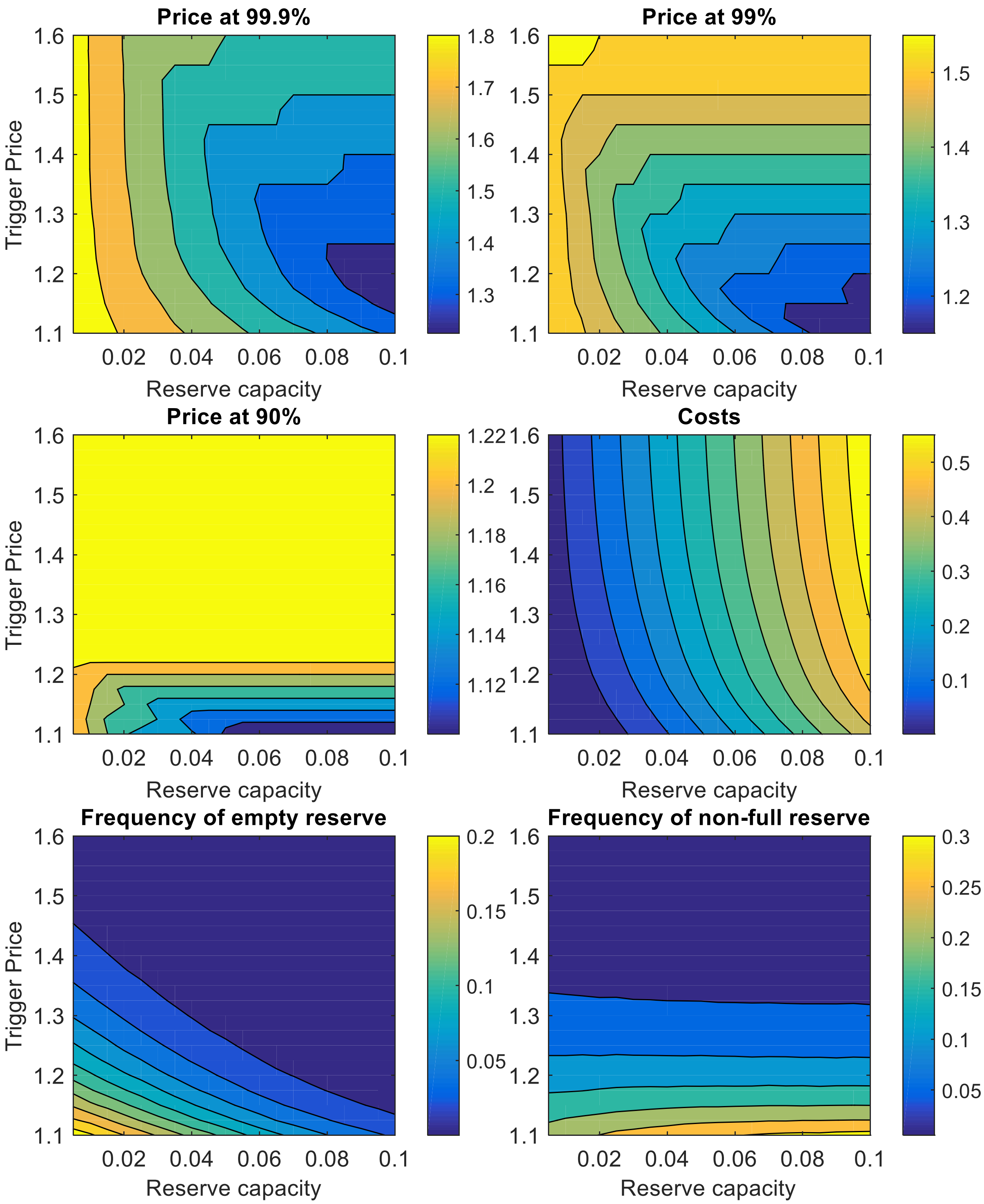

Figure 3.3: Characteristics of a common reserve dependent on its capacity and trigger price

Notes: Own illustration. The colors of the six plots show the price at the 99.9th percentile, at the 99th percentile, at the 90th percentile, the costs (in % of agricultural GDP), and the frequency of an empty as well as of a nun-full reserve, respectively. On the x-axis is always the capacity of the reserve (which can be interpreted as a share of the expected harvest), on the y-axis the trigger price (which can be interpreted as a share of the expected price, e.g. a price of 1.2 is 20% above the expected price).

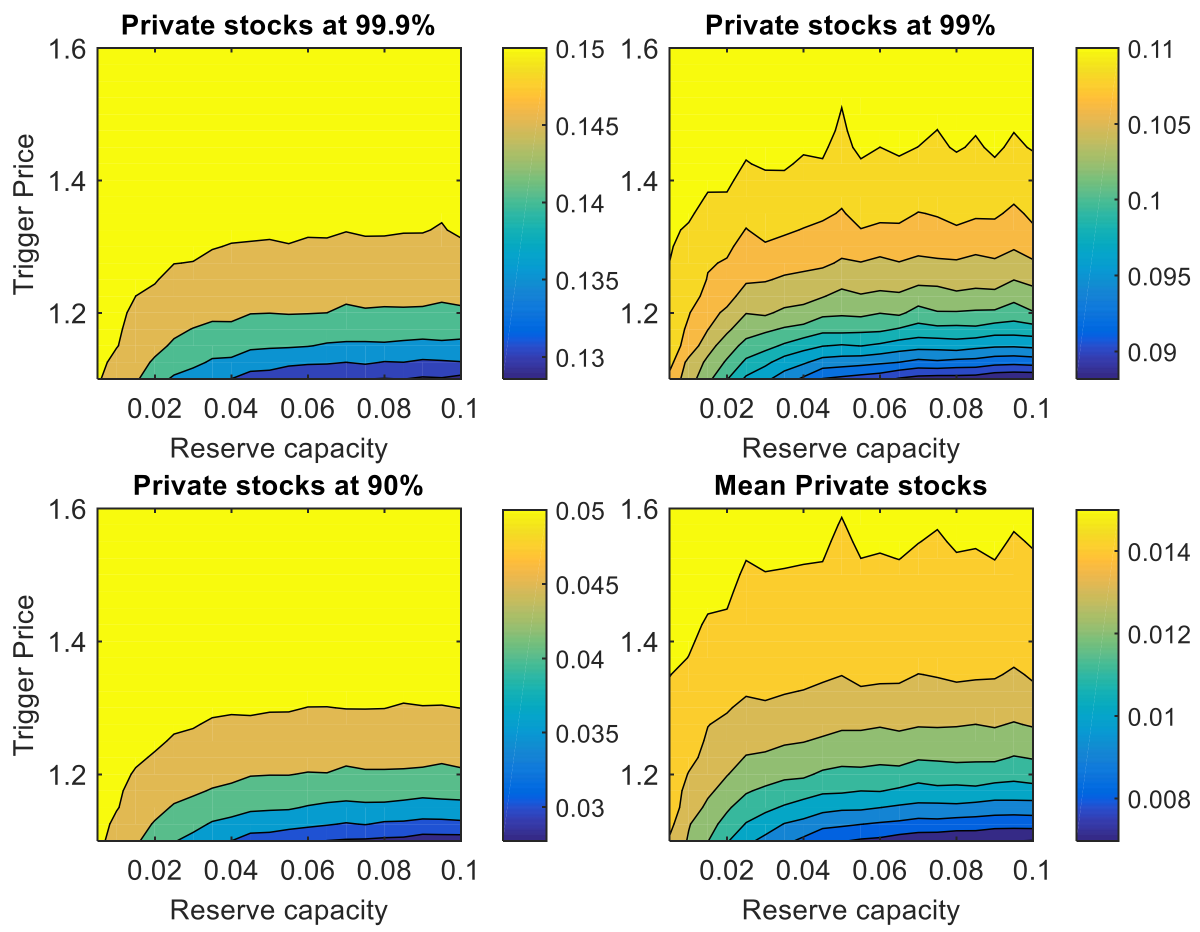

Figure 3.4: Private stocks for different reserve scenarios

Notes: Own illustration. The colors of the six plots show the private stocks at the 99.9th percentile, at the 99th percentile, at the 90th percentile, and the mean. On the x-axis is always the capacity of the reserve, on the y-axis the trigger price as in Figure 3.3. All graphs show the scenario for the common reserve with unlimited trade.

One noteworthy finding is that a reserve is not very useful to defend low trigger prices. If both the trigger price and the storage capacity are set very low, the reserve will be used frequently (bottom right of Figure 3.3). However, if now the reserve capacity is increased, the fiscal costs increase rapidly and at the same time it is getting much more likely that it is used, i.e. non-full. This is caused by the huge crowding out of private storage if the trigger price is very low and the capacity high (Figure 3.4). In this case, the government is crowding out private sector activities which would otherwise help to also stabilize market prices.

All these graphs in Figure 3.3 and Figure 3.4 allow policy makers to decide for a reserve which is optimal for their preferences on the price distribution and risks. This means that policy makers would need to decide about their price distribution and cost preferences first and then they can use these graphs to find the combination of trigger price and capacity which ensures this expectation. As an example, policy makers could define the maximum acceptable frequency of the reserve being empty (and hence the price being above the trigger price) and then find the configuration which minimizes the costs while fulfilling this criteria. An alternative example is to predefine the available budget and use this to minimize the frequency of a price at a certain percentile (e.g. a 100 year event). In general, two parameters have to be specified to obtain a unique solution.

3.5.4 Comparing efficiency and costs of a reserve and a subsidy

From a policy maker's perspective, it is important to know how the impacts and costs of a private storage subsidy compare to those of a public emergency reserve policy. Figure 3.5 shows different percentiles in different colors for the specific scenarios. As explained before, the reserve's parameters are only uniquely defined when two parameters are chosen to be optimized. Therefore, choosing a level of fiscal costs is not yet enough. Instead, two different scenarios are chosen: The dotted curves show the case where the reserve is chosen to minimize the price at the 99th percentile given the level of fiscal costs at the x-axis while for the dashed curves, the price at the 90th percentile has been minimized. The solid lines represent the storage subsidy as comparison.

As before, it can be seen that the reserves reduced the prices at the highest percentiles much more for any level of fiscal costs. However, the prices at the 75th percentile are increased while they are decreased if a subsidy is paid to private stockholders. This subsidy nevertheless increases the prices of the lowest percentiles (here the 10th percentile in magenta) which are unaffected by the reserve. Therefore, the differences of these policies are rather distinct. The dashed lines show that if the reserve is optimized to minimize the price at the 90th percentile, it still manages to reduce the prices at this percentile to levels below what can be reached through a subsidy. But even if the reserve is optimized for the 90th percentile, it is able to reduce the price in the higher percentiles significantly more than a private storage subsidy could for the same costs.

Overall, it therefore turns out that a private storage subsidy is very efficient in reducing price volatility (i.e. the standard deviation of prices) while it is very inefficient in reducing the likelihood of extreme prices which reserves can achieve at a relatively low level of fiscal costs. In particular, private storage is not able to compensate for two production shortfalls in a row, as carry-over stocks are zero when the production level is below the expected level. Thus, an emergency reserve targets consumers only while a private storage subsidy also targets risk-averse producers (besides stockholders).

It should be kept in mind that the grid size for the reserve calculations is limited – on the x-axis the capacity was varied from 0.005 to 0.1 in steps of 0.005, on the y-axis the trigger price was changed from 1.1 to 1.6 in steps of 0.025. Therefore, some fluctuations are visible in Figure 3.5 and the lines for the reserve configurations could even be slightly lower if the reserve grid density were increased. This would come at high computational costs though.

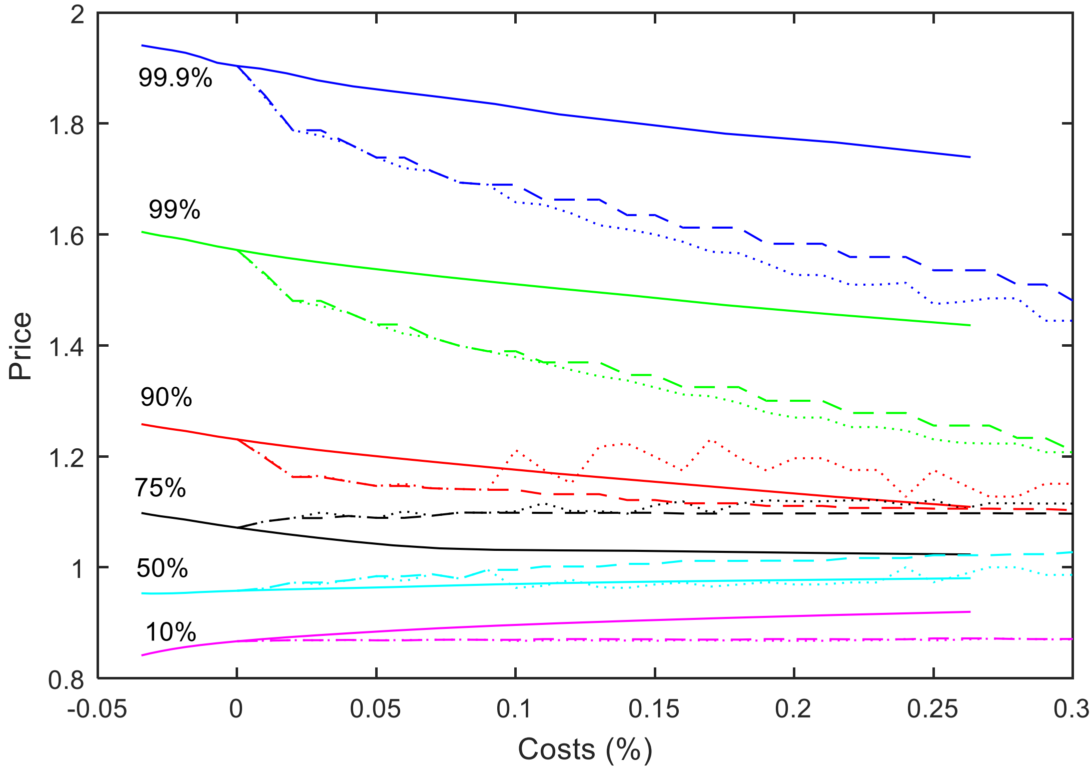

Figure 3.5: Comparison of costs and impacts of a reserve and a subsidy policy

Notes: Own illustration. The different lines show different percentiles (colors) of the price distribution depending on the fiscal costs (x-axis), expressed in % of the agricultural GDP. Solid lines represent the storage subsidy; dotted and dashed lines a reserve optimized for a minimal price at the 99th or 90th percentile, respectively. As before, a price level of 1.2 can be interpreted as 20% above the expected price because for all cases the expected prices are sufficiently close to 1.

3.5.5 The influence of asymmetric production shocks

If countries are asymmetric, this may affect the impacts and costs of the different policies. There are many ways in which the countries could deviate from one another and a full overview of these effects would go far beyond the scope of this study. However, some insights on how different parameters influence the results shall be presented. If the trade costs are increased or the previously uncorrelated harvest shocks become correlated, the benefits from cooperation decrease (not shown) but both countries will still profit from cooperating. However, this does not hold for all parameters. As an example, the influence of asymmetric production shocks is illustrated for the common reserve and free trade (Figure 3.6). The standard deviation of the production shock in country A is fixed at 6% of the average harvest whereas the standard deviation of the production shock in country B is varied from roughly 1% to 15% of the average harvest. In the absence of trade, price quantiles in A are a straight line because they do not depend on production shocks in B whereas the 99th percentile in B grows exponentially if shocks increase.

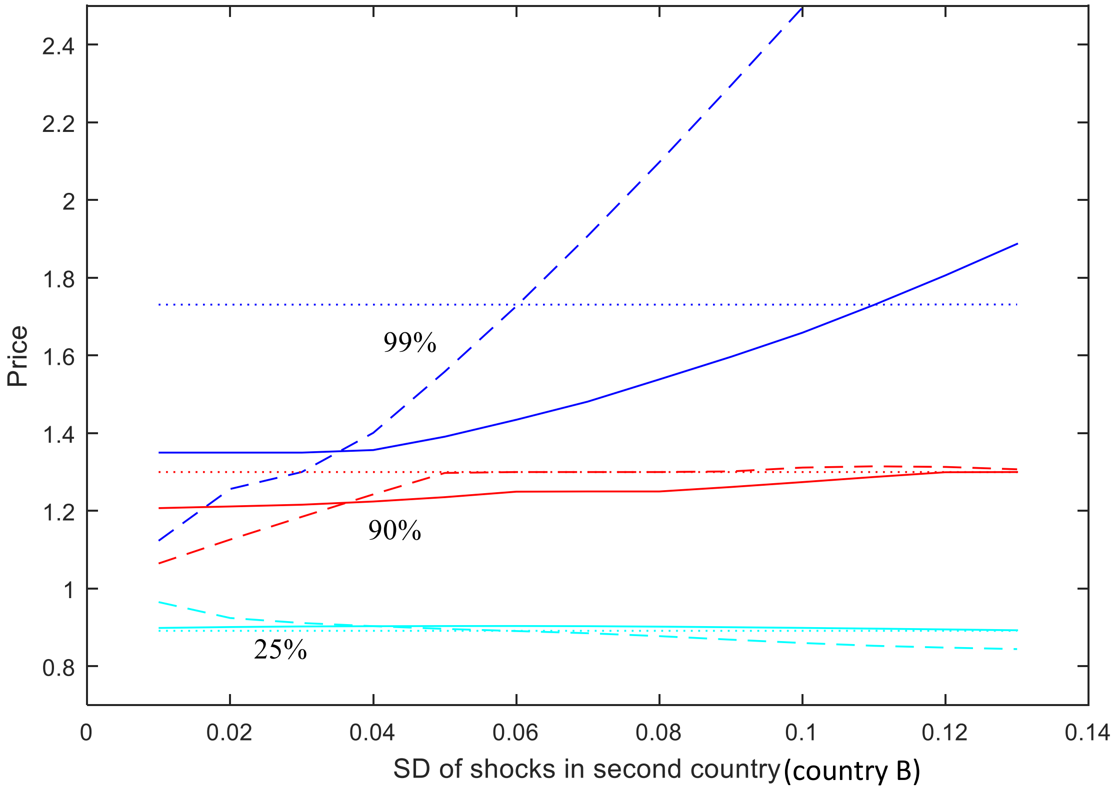

Figure 3.6: How asymmetric production shocks influence gains from cooperation

Notes: Own illustration. Different percentiles (colors) of the price distribution are shown dependent on the standard deviation of shocks in country B. The dotted line represents how prices in country A, the dashed line how prices and country B would behave in the absence of trade. The solid line represents the price in both countries when trade is unlimited.

Overall, three different regimes can be identified. Whenever the solid curve is the lower than both the dashed and dotted line, both countries would directly benefit from cooperating, i.e. they could reduce the prices at this percentile if they keep trade open. Nevertheless, if either the dashed or the dotted line is the lowest, one country benefits from cooperation while the other one loses by having to accept higher prices than in the absence of trade. In many cases, gains for the country which profits are larger than the losses faced by the other country such that compensation could be paid to achieve cooperation. Then, one country would be better off and the other one at least as well off as without trade. However, if countries are very asymmetric, the total losses may be higher than the total gains. This would be the case if the distance between the lower two prices curves is bigger than the distance between the upper two price curves for the considered percentile in Figure 3.6. Additionally, country-specific non-linear subjective welfare measures could yield the same result even if the common price would only be slightly above the insulation price for one country. In these cases, paying a compensation to incentivize cooperating is not possible. Hence, cooperation cannot be achieved if all countries are seeking to be better off. But if production can be stabilized in the shock-prone country, or if further countries can be integrated such that the collectively experienced production shocks become smaller, cooperation can become beneficial for all countries again.

For x=0.06, both countries have the same supply variability and hence the prices are the same in both countries for all percentiles if trade is blocked. As the reserve only affects the highest and lowest percentiles of the price distribution, the middle percentiles remain mostly the same in both countries if the reserve is not too big (and thus affecting the middle percentiles also). This is the reason why the 90th percentile in country B shows a kink: If the reserve is too big compared to the supply variability, the price of the 90th percentile changes but once it is sufficiently small, which is the case for a SD of shocks above 0.05 in country B, it does not change any more.

3.6 Conclusion

This study calculates for the first time gains from international trade and storage cooperation while accounting for private storage and a responsive supply. The non-linear dynamic programming, two country partial equilibrium model with private stockholders and producers with rational expectations provides a number of insights about how governments can protect their population from extreme and volatile prices. Unsurprisingly, free trade turns out to be a highly efficient and free of costs way to compensate harvest failures (scenario 2). A private storage subsidy may be an additional tool to stabilize prices. However, while it is very efficient in reducing the standard deviation of prices and thereby price volatility, it is likely to fail at compensating extreme events, i.e. massive supply shortages which may result in price spikes. Such shortages are a result of production, private stocks, and imports combined being significantly below the sum of their expected values. In contrast, a public reserve turns out to be a much more efficient way to reduce the highest percentiles of prices and therefore help in extreme events. The reserve analyzed follows very simple rules: Storing up to some capacity limit if prices are below a trigger price while releasing to prevent price increases above the trigger. This allows private market actors to easily anticipate stock acquisitions and releases. Therefore, the reserve can be set up in a way that it hardly affects private storage and only produces minimal fiscal costs. Already for 0.08% of the agricultural GDP[14], a decent level of insurance against extreme events can be reached. As comparison, Indonesia's public stock managed to stabilize prices and its costs were estimated to be 0.11% of the total GDP in 1991, a year of intensive interventions (Timmer 2013). A combination of a minor private storage subsidy and a public reserve could be an option to efficiently fight high prices and price volatility at the same time.

[14] The agricultural GDP here serves only as a comparison, i.e. to better illustrate the level of the costs. However, the costs can be expressed in absolute terms without referring to the agricultural GDP.

Another consideration for a policy maker is that a private storage subsidy may heavily impact trade whereas an emergency reserve hardly does. While it could be useful to limit the need for trade if infrastructure is bad, it also implies that in case of large supply shortfalls there may be fewer companies ready to start importing. Thus, it may increase impacts of extreme production shortfalls. Furthermore, private storage has also been argued to provoke stock hoarding and create speculative bubbles (a discussion of this issue is found in Dorosh and Rashid 2012; Galtier 2014; for empirical cases compare Ravallion 1987; Sen 1980). This is another argument for keeping a public emergency reserve.

The results further show that if the policies of the countries are not aligned, no such measures, be they public or private storage oriented, can exploit their full potential. If trade is not limited and only one country has a reserve, the results show that benefits of this reserve will leak into the other country while the costs do not. Both countries would then benefit from the insurance mechanism which is maintained and paid for by one country only thereby creating a free rider problem. But countries looking for protection from extreme events can set up their own reserve while restricting exports when the reserve is used, thereby preventing leakages from the reserve into foreign markets. If countries want to cooperate but for logistical or other reasons the maintenance of a reserve is easier in one country, the other could pay compensation as the protection from supply shortages is almost equally shared (scenario 4). This works as long as the asymmetries between the countries are not too big. If they are, the losses for one country may become bigger than the gains for the other resulting in a situation where compensation payments cannot incentivize free trade for all.

These results are of high relevance for the ongoing WTO negotiations. As shown, countries face no or few incentives to commit to free trade if they have domestic price stabilization policies in place because benefits would leak into world markets while costs do not. The results also showed that very high prices may be realized if some countries have stabilization policies in place and use trade restrictions while other countries rely on free trade without public interventions. In this scenario, prices in the latter group of countries can rise well above levels which would be achieved if all countries would refrain from intervening into markets in any way. Therefore, this behavior, public stocks combined with trade restrictions, can explain the high prices observed during the world food crisis in 2007/08. However, the costs and negative welfare impacts of a failing Doha round or of excluding agriculture from it are huge (Bouet and Laborde 2010; Laborde and Martin 2012). One potential solution could be to allow some flexibility for key products, an argument usually proposed based on political pressure for politically sensitive products. But even this is likely to show severe adverse impacts (Jean et al. 2010). This flexibility would correspond to export tariffs or quotas which can be introduced, but are limited according to pre-defined criteria. Hence, it is related to the scenarios 5, 6, and 7 of this model. As it was shown, applying flexible rules helps to keep the borders open most of the time and thus limits the occurrence of extreme events. However, it was also shown that if there are countries with public stocks which limit exports, prices in countries without public stocks can increase dramatically (scenario 7). It that situation, it can be better to not maintain any public stocks but always keep trade unlimited. This corresponds to scenario 2 of this model which shows indeed a higher level of price stability as scenario 7. In the real world, the price stability may depend on how the production and its variability differ between the countries that would impose such restrictions and those which do not. Another challenge arising from flexible rules is that they may be hard to monitor. However, if reserves would be following simple rules, as in this study and generally suggested, then it would be possible to pre-define strict criteria for the flexible trade rules, e.g. market prices reaching certain levels (accounting for their trend). This way, rules according to scenarios 5, 6, and 7, i.e. pre-defined export quotas or tariffs, could be monitored by the WTO and violations could be identified and sanctioned by the WTO dispute settlement mechanism. Nevertheless, if there are many countries without public interventions, prices in these countries can become less stable (scenario 7) and therefore this may not be the preferred option.

Two potential solutions remain which allow combining price stabilizing market interventions while at the same time incentivizing free trade and thereby profiting from the comprised welfare gains and overcoming the collecting action problem of insulating policies: First, an international emergency reserve financed by the international community that provides a sufficient level of protection for all countries (an extension of the proposal from von Braun and Torero 2009). This would correspond to scenario 8 of this model and it was shown that extreme prices are particularly rare in this scenario. Yet, achieving a mutual agreement on stocking policies and on sharing the fiscal burden seems very difficult if not impossible. The second option is to introduce a scheme for compensation payments to countries with price stabilization policies which would ensure compensation for not imposing trade restrictions in time of crises. Hence, the international community would need to agree on sharing the fiscal costs of those price stabilization measures from which all countries also benefit when global production falls short. Unfortunately, this kind of mutual agreement does not seem any easier to achieve. A non-global alternative could be the formation of country groups which build common reserves (or use other measures), ensure free trade within the group, and use restrictive trade policies only to prevent leakages into foreign markets. Such country groups might be easier to form, as countries with a more common understanding of impacts of volatile and high prices and views on stabilization policies are more likely to commit to mutual agreements. Partly, such groups exist or are in the process of being implemented for the ECOWAS countries (ECOWAS Commission 2012) and ASEAN plus three (Briones 2011). Nevertheless, a substantial share of potential global welfare gains from free trade is lost if only interest groups cooperate.

The WFP buys a large share of their acquired 2 million tons of food per year as close as possible to where it is needed (WFP 2016). This allows saving time and money for transportation and helps the local economies (ibid.). However, when there is a supply shortage evolving, buying grains from other surplus countries and shipping them to the crisis region may be preferable in order to prevent price surges (this could correspond to a targeted trade subsidy in the model). Such as strategy is partly applied and the WFP has even been awarded an international supply chain award for their comprehensive strategy (WFP 2014). The WFP keeps around a million tons of food in their 650 warehouses and an additional 120.000 tons in warehouses which are managed by humanitarian partners (ibid.). It procures food through competitive bidding processes to achieve the best possible prices (WFP 2013). Nevertheless, the WFP operations are small compared to the total global grain markets. As food for humanitarian emergencies is often exempted from export restrictions, it may therefore be an option to upscale the WFP operations. Thus, more grains could be provided for import-dependent countries when they lose access to imports due to export restrictions imposed by major producer countries. While this would not solve the general beggar-thy-neighbor problem, it could allow more protection for the most vulnerable countries and regions in times of need.

Limitations of this study arise from the model specification. In particular, the conclusions about how asymmetry between countries affects the gains from cooperation are very limited. Hence, results are not intended to provide a concrete quantitative guidance on how to set up a reserve for a specific country but rather to illustrate the behavioral characteristics of and interactions between different policies. Most importantly, conclusions about the emergency reserve are restricted to reserve policies which can be described by the chosen scheme or which behave sufficiently similar. However, other policies for a reserve could be chosen and would need an own investigation. Finally, limitations arise from the design of the model and the partial equilibrium framework. For example, interactions with other sectors of the economy were not considered, private stockholding may happen for other reasons than profit-maximization, and markets may be incomplete and their dynamics non-stationary.

Past research on international storage-trade cooperation has typically ignored the effects of public reserves on private storage and trade. This study illustrates what effects can be expected from economic theory for different stabilization measures and how these depend on different parameters. Given the occurrence of rare but extreme price spikes (compare e.g. Deaton and Laroque 1992), this study supports the calls for considering public stockholding programs which can support private storage. Future research should therefore provide specific regional case studies which identify such effects for specific sets of countries. In addition, more knowledge is required on how asymmetry influences potential gains from cooperation, e.g. how the benefits depend on the correlation of the production, the relative size of the countries, and the demand elasticity of the consumers. Furthermore, more research is needed on how agreements can help to overcome incentives to default, i.e. to impose trade restrictions. For example, if countries cooperate by having a common reserve, incentives to impose trade restrictions may be reduced. A substantial risk of retaliation may have a similar effect. Apart from that, studies on nutritional and welfare impacts of high and volatile prices should receive more attention on the research agenda. The full social costs, including nutritional impacts, of high and volatile prices still remain under-investigated. More knowledge in this field might also pave the way for game theoretic analyses about how countries can find agreements if objective functions and perceptions of how prices impact welfare vary.

4 Linking Theory and Empirics: Derivation and Empirical Testing of a Surrogate Model for Private Storage[15]

4.1 Abstract

The competitive storage model (CSM) has evolved as the workhorse in numerical analyses of price stabilization through private storage and recent evidence has supported its empirical validity. However, several shortcomings prevail. The numerical implementation of the model remains very complex and is limited to settings with very few state variables. Therefore, only one or two countries can typically be considered and policy measures need to be implemented in very simplified manners. Furthermore, approaches to empirically validate the CSM have focused on the distribution of prices but ignored actual stock levels. Finally, the CSM only indirectly allows empirically quantifying stock determinants. This study addresses these issues by developing a surrogate model for drivers of competitive storage. The reduced-form model is obtained from a so-called response surface methodology which econometrically relates the stock data generated by the CSM to various input parameters and the state variables, i.e. global and domestic supply and income. This approximation allows the characterization of grain stockholding by a piece-wise linear function for a broad set of parameters and model assumptions and can therefore be implemented in high-dimensional modelling exercises. When tested with generated data, the model turns out to be highly precise and flexible. It is then applied to empirical stock data for 32 countries using a non-linear least-square panel regression. This provides an alternative way for the empirical validation of the CSM which, as a novel feature, accounts for actual stock levels. Results of empirical estimations provide for the first time a direct comparison of the empirical and theoretical influence of different parameters.

4.2 Introduction

Measures to stabilize grain prices need to be based on insights into how markets function. For ensuring sufficient grain supplies the main actors of interest are producers, traders and stockholders, be they smallholders or big commercial agents. Therefore, knowledge about the behavioral determinants of private stockholders is an important prerequisite for evaluating any type of public intervention. The competitive storage model (CSM) has become the workhorse in theoretical models involving private profit maximizing stockholders. There are also more simplified models circulating (e.g. stocks as a fixed share of supply), but these usually have

[15] Earlier versions of this work have been published in the conference proceedings of the ECOMOD conference 2015, Boston, as Brockhaus J., Kalkuhl, M. “Drivers of private grain storage. A computational-economics and empirical approach” and of the GEWISOLA 2014, Göttingen, (published as “Schriften der Gesellschaft für Wirtschafts- und Sozialwissenschaften des Landbaues e.V., Band 50, 2015) under the name “Empirical Investigation of Private Grain Stock Determinants”.

very simplistic assumptions about the price expectation formation process. The CSM has enabled the acquisition of numerous insights about possible market interventions, though these are typically based on theoretical models. Due to its theoretical importance, interest in testing the empirical validity of the CSM has been and still remains high.

After the establishment of storage-trade models (Miranda and Glauber 1995; Williams and Wright 1991), many authors have used the CSM to simulate market prices and then compare the obtained price characteristics to empirical price data in order to tests the model's empirical validity[16]. Deaton and Laroque (1992) have been able to predict the price behavior for thirteen commodities including rare but violent price explosions. However, they argue that their model cannot explain the high degree of autocorrelation observed in the data. Even after changing from a GMM estimation to fitting the competitive storage model directly, the high level of autocorrelation could not be modelled (Deaton and Laroque 1996, 1995). Miranda and Rui (1999) found this issue can be solved by employing a supply of storage function which allows negative intertemporal price spreads if stocks are positive and by using a nested maximum likelihood estimation technique. In a similar vein, the incorporation of a convenience yield, i.e. the attribution of an intrinsic value to the possession of stocks (Brennen 1958; Working 1949), has allowed replicating U.S. corn prices (Peterson and Tomek 2005). However the concept of convenience yields has always been controversial (compare e.g. Deaton and Laroque 1996). In a further step, the model was shown to produce consistent results which support the model's validity if output and demand trends, yield shocks, as well as time dependent interest rates are considered (Miao et al. 2011). Finally, Cafiero et. al (2011) showed that the model from Deaton and Laroque (1995, 1992) may even replicate the high degree of autocorrelation by only applying a much finer grid of state variables on which the model is solved. This improved the precision of the results and yielded a much higher degree auf autocorrelation. Cafiero et. al (2011) also illustrate how more realistic assumptions on parameters, e.g. a less price-sensitive demand curve and lower storage costs, can also solve this issue. Overall, today there seems to be substantial evidence for the empirical relevance of the CSM. However, in all these analyses, only the prices and price stability over time have been considered but to the best of the author's knowledge no approaches have been made to estimate the drivers of private grain stocks considering actual stock levels. Yet, without providing any further details, Deaton and Laroque (1996) have mentioned that a different approach would be taken if actual stock data is used. This work presents such an approach.

This study develops a new method to empirically test the CSM and directly identify drivers of private grain storage. Therefore, this study compares the dependency of stocks on different parameters in the theoretical simulations and for the empirical data. The idea is to first solve

[16] Prices are usually easier to observe than stocks which may have driven earlier empirical validity tests.

the model numerically for a specific set of parameters. Then, policy functions are derived, i.e. the stock levels are expressed by the state variables, i.e. availabilities and income levels. As it is not a priori clear what functional form should be assumed for the dependence of stocks on the state variables, at first qualitative arguments for a specific form are presented. These are then econometrically verified using a so-called response surface fitting procedure (Box and Wilson 1951; Gorissen et al. 2010; Hendry 1984). This methodology allows analyzing the relationship between several explanatory variables (here the state variables) and a response variable (stocks). This procedure is necessary because no analytical solution exists and therefore grid points of the numerical solution need to be fitted with a well-defined and theoretically founded reduced-form equation. As a result of the approximation of the policy function, a surrogate reduced-form model for competitive storage is obtained. In contrast to earlier studies, it does not model prices but rather stock levels directly. On the one hand, this requires data on actual stock levels while on the other hand it also allows finding a much simpler reduced-form equation. Prices are highly non-linear and even on small intervals they can hardly be approximated by piece-wise linear functions (compare Figure 4.1). The closing stocks in contrast, can very well be approximated by a piece-wise linear function. This non-linearity of prices but piece-wise linearity of stocks is, however, also a result of the model assumptions, in particular of the iso-elastic demand function. Nevertheless, this behavior is observed for several of the typical ways to specify similar models.

Monte-Carlo methods are used to specify the impact of different model parameters on the results, i.e. the stocks. This means that the model is solved for a wide range of parameters and the influence on the response variables is econometrically quantified. The derived reduced-form surrogate model which is obtained this way is then applied to empirical data in order to identify which variables are drivers of private grain stocks in the real world. This final reduced-form storage equation can be also used in high-dimensional modelling exercises. In this case it eliminates the need to solve the non-linear rational expectations market equilibrium which otherwise typically comes with the “curse of dimensionality” (Bellman 1957). This “curse” is a permanent source of trouble in dynamic programming problems, particularly if non-linear equations are included as it is the case for the CSM.

Of course, this procedure comes with its own shortcomings. Most importantly, data which distinguish between private and public stocks is mostly missing. Therefore, the empirical analysis can only be based on the total stock data. However, different measures are undertaken to ensure that the results are not distorted by public stocks (compare section 4.7.2 for details). Most importantly, only developed countries which have very low public stocks and rarely use them are included in the analysis. Section 4.7.2 also argues that very small public stocks typically have a minimal impact on private stockholding activities. Only considering countries without any public stockholding program could fully resolve the issue but this is empirically infeasible due to a lack of such countries. This approach would come at the costs of a substantial reduction in the number of observations which is expected to have a more distortive effect on the results. Another limitation is the negligence of trade distortions which are typically impossible to quantify for a broad set of countries. Furthermore, for a full validity test of the whole model rather than testing only the influence of specific parameters, the model would need to be calibrated to each specific country-crop combination to reproduce specifically the moments of the stock distributions.

The remainder of this chapter is structured along four crucial steps. First, in section 4.3 the theoretical model is presented including its calibration parameters. This is the theoretical benchmark model which is used to generate stock data for a wide set of parameters and supply situations, i.e. a Monte-Carlo simulation method is applied. The model includes one country with supply and income shocks which can store and trade with the rest of the world. Supply shocks can also occur in the rest of the world and indirectly affect the country. Second, in section 4.5 the dependency of the results (the stock data) on input parameters is illustrated by first explaining the qualitative behavior of grain stocks according to visualizations of stocks and then developing a tractable reduced-form storage equation that quantitatively captures these dynamics. Third, in subsection 4.6 the quality of the approximation using the R^2 from non-linear least-square fits on the generated data from the first step is evaluated. Forth, section 4.7 applies a non-linear least square regression to estimate the reduced-form storage equation using actual storage and supply data from 32 countries. Major findings and their policy implications are summarized in section 4.8.

4.3 Theoretical model

The model specification follows Gouel (2011) or Gouel and Jean (2015) but differs in explicitly including the rest of the world as a second country and in incorporating income shocks while excluding public stocks. It is very similar to the model presented in chapter 3. Nevertheless, the main differences lie in the incorporation of income shocks, exclusion of public interventions, be they trade or storage oriented, and neglection of fiscal costs and extreme events. The model describes a homogeneous agricultural product that can be produced, consumed, and stored in both countries as well as traded between them. It is a partial equilibrium dynamic programming model with discrete annual time steps.

4.3.1 Stockholders

The behavior of the stockholders is based on the competitive storage model. Each country $i \in \{A, B\}$ has a single representative stockholder who is risk neutral and acts competitively. The stock quantity $S_{i,t}$ is purchased at price $P_{i,t}$ in country i and then carried from period t to period $t+1$, where it is sold for price $P_{i,t+1}$. Storage losses $(1-\delta_i)$ occur and constant marginal storing costs k_i apply. Hence, the stockholders are modelled in the same way as in chapter 3 and as described in section 3.3.1. The only difference is that the subsidy m_i is zero for both countries.

4.3.2 Producers

Each country has one representative producer who is risk neutral and makes the planting decision $H_{i,t}$ one period before the harvest in period $t+1$ where they experience a random yield shock $e_{i,t}$. Thus, the producers are modelled in the same way as in chapter 3 and described in section 3.3.3.

To limit the number of state variables, the carry-over stocks and the harvest can be combined to one state variable per country, availability $A_{i,t}$ with

$$A_{i,t} = (1 - \delta_i)S_{i,t-1} + H_{i,t-1}e_{i,t}. \tag{4.1}$$

This is the availability before trade takes place.

4.3.3 Trade

A representative trader uses all spatial arbitrage possibilities and trades competitively between both countries A and B. Thus, trade is modelled as in chapter 3 and described in section 3.3.4. However, there are no trade quotas in this model such that $X_i = \infty$. Furthermore, there are no import tariffs, i.e. $\phi_{i,t} = 0 \; \forall \; i, t$, and trade costs are described by the character Θ.

4.3.4 Consumption

In contrast to chapter 3, consumers in this model suffer from income shocks. Each country has consumers which consume according to an isoelastic demand function

$$\mathrm{D_i}\left(\mathrm{P_{i,t}}, Y_{i,t}\right) = \gamma_i P_{i,t}^{\alpha_i} Y_{i,t}^{\eta} \tag{4.2}$$

with normalization parameter γ_i, price elasticity $-1 \neq \alpha_i < 0$, and income elasticity $\eta_i \neq 1$. The income $Y_{i,t}$ is assumed to be constant in the rest of the world, i.e. country B, while in country A it is subject to random, normally distributed shocks with mean 1 and variance σ_i^y. For simplicity, the consumers always consume the current income and do not save, hence, consumers' savings can be ignored. Otherwise, these would need to be considered as additional state variables and a further maximization problem would need to be solved. As a result, the current income in country A, $Y_{A,t}$, is the third state variable of the model besides $A_{A,t}$ and $A_{B,t}$.

4.3.5 Market equilibrium

The shocks are considered at the beginning of each period so that equation (4.1) and the realization of the income shock in country A provide the state variables. The market equilibrium condition is

$$A_{i,t} - X_{i,t} + X_{-i,t} = D_{i,t}\left(P_{i,t}, Y_{i,t}\right) + S_{i,t} \; . \tag{4.3}$$

Therefore, when the model is solved numerically, a recursive equilibrium needs to be found, i.e. a set of functions $S_{i,t}(A_{i,t}, A_{-i,t}, Y_{A,t}), H_{i,t}(A_{i,t}, A_{-i,t}, Y_{A,t}), P_{i,t}(A_{i,t}, A_{-i,t}, Y_{A,t})$, and $X_{i,t}(A_{i,t}, A_{-i,t}, Y_{A,t})$ which describes the dependency of these response variables on the state variables. To obtain this set of equations it is assumed that the stockholders, producers, and the trader maximize their profits according to equations (3.1), (3.9) and (3.11), respectively, while the market clears according to equation (4.3) and the transition equation (4.1) holds.

4.4 Calibration

Calibration parameters including explanations are provided in Table 4.1. The expected value of all shock variables is 1. The model is solved on a $9 \cdot 9 \cdot 9$ grid of the state variables for each set of the parameters. This resolution is not particularly high and therefore the precision of the results is somewhat limited. However, as the behavior will be shown to be piece-wise linear, the resolution is sufficient. The mean error of the stock levels seems to be only around 3% (compare appendix 8.2). Furthermore, it is necessary to impose this limit on the resolution in order to preserve computational requirements which can still be handled. From all the parameters, five parameters are varied to test their influence on the response variables. These parameters include the interest rate, the relative country size, the standard deviation of supply shocks, and the demand as well as supply elasticity. They all refer to country A. The choice of these parameters is based on the availability of cross-sectional data for the later application to real-world stock data. For each of these parameters, three different values have been used, except for the interest rate, for which only two parameters were used. This leads to $2 \cdot 3^4 = 162$ different sets of parameters. Since for each parameter set the model is solved on a $9 \cdot 9 \cdot 9$ grid of the state variables, $2 \cdot 3^4 \cdot 9^3 = 118098$ observations are generated in total. The simulations are conducted in MATLAB using the RECS solver (Gouel 2013a) and the CompEcon toolbox (Miranda and Fackler 2011).

4.5 Simulation results

The aim of this study is to analyze drivers of private grain storage which as a first step involves obtaining a qualitative understanding of how private storage generally behaves within a broad set of parameters and model assumptions. In a step-by-step procedure, the analysis starts with a very simplified model and successively adds more extensions to derive the reduced-form equation for the full model. This reduced-form equation is then used as the starting point for a response surface fitting procedure in section 4.6.

4.5.1 One country without income shocks

First, the case of a single country without income shocks is considered (Figure 4.1). The upper panel of Figure 4.1 represents the so-called “storage rule” for different assumptions about the variability of domestic harvests. The expression “storage rule” just refers to the behavior of stocks which is obtained from the numerical simulations under the modelled assumptions (such as profit-maximizing, risk-neutral stockholders). It could just be described as the behavior of stocks. However, as it is commonly referred to as the storage rule, the same convention is adopted here.

It turns out the storage rule has a kink, so it is zero before a certain threshold and then it increases with availability. The kink varies with the standard deviation of supply shocks but the slope remains nearly constant. To be precise, the slope is not linear but convex (compare e.g. Gouel 2011; Williams and Wright 1991). But once the availability is above the threshold, the curve can be approximated to a certain extent by a linear function. Figure 4.2 again illustrates the dependence of the closing stocks on the availability but here the storage costs and the interest rate in country A are varied as indicated in the graph. In this case, not only is the threshold changed when storage takes place, but so is the slope of the storage rule. For high storage costs or a high interest rate, the slope of the storage rule decreases (the interest rate behaves similarly to the storage costs as it increases the (opportunity) costs of storage). This implies that higher availability does not increase the stocks as much as in the baseline scenario which is in line with expectations. On the one hand, these results justify the approximation of stocks by a piece-wise linear function, as will be discussed in the subsequent paragraphs. On the other hand, the influence of individual parameters on the results is not yet clear at this stage and will be illustrated and numerically derived afterward.

Based on the results of these simulations, one can conclude that the storage behavior can be approximated by a straight line above a certain threshold. However, the slope of the line and the threshold may change, depending on the underlying parameters. This is the result from the simulations, but there is no qualitative a priori explanation, why this result is observed. As a next step, the influence of all six parameters on the shape of this piece-wise linear storage rule is illustrated. Figure 4.3 shows how the intercept, i.e. the position of the kink in the storage rule, changes when parameters are varied. To obtain the graph, all parameters are set to their standard values and then, consecutively, the different parameters are varied while holding the others constant.

The results (Figure 4.3) indicate that the threshold increases if the interest rate, the storage costs, the storage losses, or the supply elasticity increase; meanwhile it decreases if the standard deviation of shocks or the demand elasticity increase. Figure 4.3 shows all these results by indicating the different parameters which are varied (interest rage, storage costs, …) in different colors and with different line styles. As before, the intercept changes nearly linearly with these parameters, except for the standard deviation of supply shocks where it is closer to a quadratic form.

Table 4.1: Calibration Parameters for the simulations

Parameter	Variable	Value(s)	Comments
Supply elasticity in ROW	$1/\mu_B$	0.2	Value from Gouel, Gautam & Martin (2014)
Supply elasticity in A	$1/\mu_A$	0.2; 0.3; 0.4	Variation of values to cover range in FAPRI and USDA databases
Price elasticity in ROW	α_B	-0.27	Typical value
Price elasticity in A	α_A	-0.08; -0.16; -0.32	Variation of values to cover range in FAPRI and USDA databases
Storage costs per unit	k	0.06	Common value for such models
Interest rate in ROW	r_B	0.03	Typical rate
Interest rate in A	r_A	0.07; 0.15	Variation to cover main range in the World Bank data
Trade costs	Θ	0.1	Common value for such models
Income elasticity in ROW	η_B	Income is fixed	
Income elasticity in A	η_A	0.5	Common value for such models
Normalization par. in ROW	γ_B	2	Describes relative scaling to parameter in A
Normalization par. in A	γ_A	0.02; 0.1; 0.2	Variation in size: 1%, 5% and 10% of rest of the world size.
SD (standard deviation) of supply shocks in ROW	σ_B	0.065	Estimated for the world wheat production from USDA data
SD of supply shocks in A	σ_A	0.02; 0.06; 0.12	Variation to cover main range in USDA data
SD of in. shocks in ROW	σ_B^y	Income is fixed	
SD of income shocks in A	σ_A^y	0.035	Estimated from SD of GDP fluctuations from Hodrick-Prescott-filtered trend from World Bank database
Production normalization parameter in ROW	h_B	$1/(1+r_B)$	
Production normalization parameter in A	h_A	$1/(1+r_A)$	
Parameters for solving and simulating			
Number of nodes for each shock variable		7	
State variables grid for which the solutions are calculated		9 for each state variable (from 0.7 to 1.3)	This is the grid on which the solutions are calculated for each set of parameters. (higher for simulations with only one country)

Notes: Own illustration.

For each of these models, the OLS estimator was used to estimate the slope coefficient of the strictly positive part of the storage rule. As a result, it is possible to evaluate how the slope coefficient changes when the parameters are varied (Figure 4.4). The slope decreases if the standard deviation of shocks, the interest rate, the storage costs, or the storage losses increase or if the supply elasticity or demand elasticity decrease. While the dependency is not fully linear, a linearization is still tested. To evaluate fit of the piece-wise linear approximation of the storage rule, the R^2 for each approximation was calculated (Figure 4.5). As the R^2 is always above 0.998, the linear line turns out to be a very good approximation for the strictly positive part of the storage rule in all of the tested scenarios. For each of the points from the lines in Figure 4.4 and Figure 4.5, an OLS model was estimated. Overall, these are hundreds of models that are estimated. Therefore, it is not possible to show the results for all estimated models but only the estimated coefficients for the slope are depicted (Figure 4.4) as well as the corresponding R^2s (Figure 4.5) to evaluate the goodness of fit.

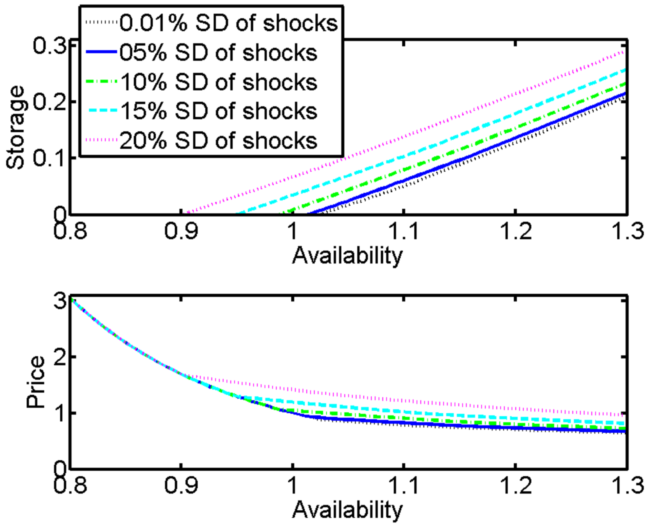

Figure 4.1: Closing stocks (above) and prices (below) in country A

Notes: Own illustration. Stocks and prices can be interpreted as absolute values or in relative terms as a share of the expected harvest (≈ 1)or expect price (≈ 1), respectively. They are expressed in dependence of availability in A (total supply = production + opening stocks) for a fixed set of parameters. The different curves represent different values of the standard deviation of harvest shocks in A to show how this affects the storage rule.

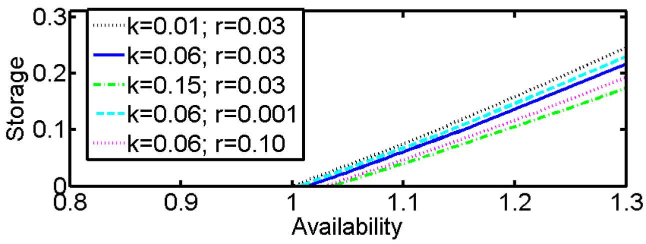

Figure 4.2: How storage costs k and interest rate r affect closing stocks

Notes: Own illustration. The way of illustrating the results is as in Figure 4.1. Implications are discussed in the text.

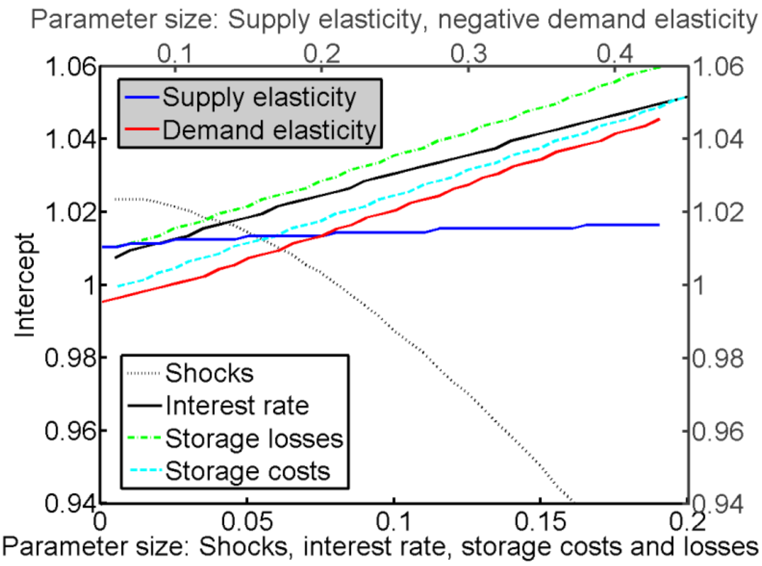

Figure 4.3: Dependency of the storage rule's intercept

Notes: Own illustration. The SD of production shocks, interest rate, storage costs, and storage losses are plotted using the bottom x-axis, the supply elasticity and negative demand elasticity are plotted using the top x-axis.

If a piece-wise linear reduced-form approximation is chosen, the response function for stocks in A can be written as (with some parameters a and b for the slope and the intercept)

$$S_A(A_A) = \begin{cases} 0 & \text{if } A_A < \tilde{A}_A = -\frac{b}{a} \\ aA_A + b & \text{if } A_A \geq \tilde{A}_A = -\frac{b}{a} \end{cases} \tag{4.4}$$

or, in a form that can be used for a least-square estimation, as

$$S_A = \max(0, aA_A + b) \tag{4.5}$$

Based on the results depicted in Figure 4.3, Figure 4.4, and Figure 4.5, it was argued that the influence of the individual parameters on the intercept and slope of the storage rule is linear. This implies that the parameters a and b can be represented as a linear combination of the individual parameters, each of them multiplied by an unknown coefficient which determines the linear dependency. Thus, the impact of the model parameters on the intercept b and the slope a of the storage rule can expressed as $a = a_0 + a_r r_A + a_\mu 1/\mu_A + a_\alpha \alpha_A + a_\gamma \gamma_A + a_\sigma \sigma_A$, and $b = b_0 + b_r r_A + b_\mu 1/\mu_A + b_\alpha \alpha_A + b_\gamma \gamma_A + b_\sigma \sigma_A$. This allows applying the storage model to various contexts that differ in their parameter constellation (e.g. due to crop or country-specific characteristics) by fitting:

$$S_A = \max\big(0, (a_0 + a_r r + \cdots)A_A + (b_0 + b_r r + \cdots)\big) \tag{4.6}$$

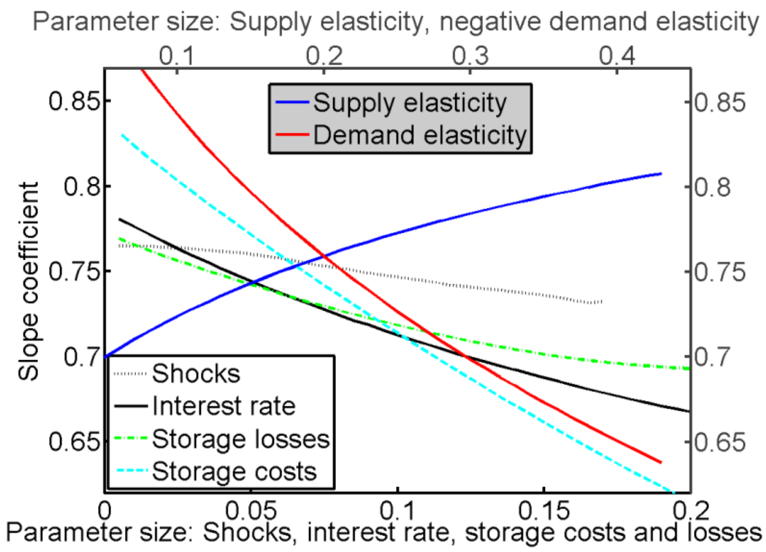

Figure 4.4: The dependency of the slope coefficient

Notes: Own illustration. The slope coefficient was obtained from a linear OLS fit on the positive part of the storage rule with the regression being performed for each set of parameters. The SD of production shocks, interest rate, storage costs, and storage losses are plotted using the bottom x-axis, the supply elasticity and negative demand elasticity are plotted using the top x-axis.

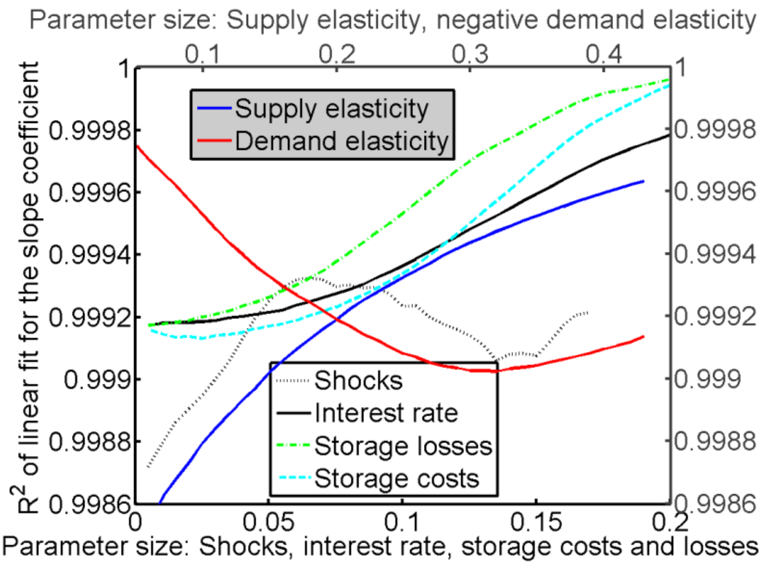

Figure 4.5: R^2 of the linear OLS fit for the positive part of the storage rule

Notes: Own illustration. The very good fit justifies the approximation of the storage rule by a piece-wise linear function with a kink with the position of the kink and the slope coefficient depending on input parameters. The above graph shows hundreds of fitted models, i.e. for each point in the graph, one model was fitted. Thus, it is not possible to show the results for each estimated model but only the resulting coefficients for the slope (Figure 4.4) and the corresponding R-squares are shown (this Figure).

4.5.2 Two countries without income shocks

Extending the model to two countries makes the response variables dependent on two state variables, availability in A and B (Figure 4.6). Again, B represents the rest of the world. Clearly, storage only takes place in regions of excess supply which is in line with what was expected as trade is costly and both regions are, on average, self-sufficient in this simulation. Therefore, excess supplies will be stored in the region where they are produced to either use them in the same region later without having any trade costs or to use them in the other region later so that trade costs only occur once. If there is little supply in B but excess supply in A, there will also be little storage in A but instead exports to B will be high. In case of excess supply in both regions, the storage rule for one region is (nearly) independent of the level of excess supply in the other region. The slope above the threshold itself seems to be independent of the availability in country B which has been verified by comparing the slope coefficients for different levels of availability. Overall, these observations lead to the following mathematical description of the reduced-form storage rule for the case of two countries:

$$S_A(A_A, A_B) = \begin{cases} 0 & \text{if } A_A < \tilde{z}(A_B) \\ aA_A + b\left(1 + \tilde{z}(A_B) - \tilde{A}_A\right) & \text{if } A_A \geq \tilde{z}(A_B) \end{cases} \tag{4.7}$$

$$\text{with } \tilde{z}(A_B) = \begin{cases} \tilde{A}_A & \text{if } A_B > \tilde{A}_B \\ \tilde{A}_A - \beta\left(\tilde{A}_B - A_B\right) & \text{if } A_B \leq \tilde{A}_B \end{cases} \tag{4.8}$$

$$\text{and } \tilde{A}_B = \theta = \theta_0 + \theta_r r_A + \cdots,\ a = a_0 + a_r r_A + \cdots,\ b = b_0 + b_r r_A + \cdots,$$
$$\text{and } \beta = \beta_0 + \beta_r r_A + \cdots$$

Here, $\tilde{A}_A$ is the point for which $0 = S_A\left(A_{A,1}, \max A_B\right) = S_A\left(\tilde{A}_A, \max A_B\right) < S_A\left(A_{A,2}, \max A_B\right)$ for any $A_{A,1} \leq \tilde{A}_A < A_{A,2}$. The $a, b, \beta,$ and θ do, as before, consist of six terms: One constant term with subscript zero and additionally one term for each parameter, so e.g. $a = a_0 + a_r r_A + a_\mu 1/\mu_A + a_\alpha \alpha_A + a_\gamma \gamma_A + a_\sigma \sigma_A$. Here and in the subsequent sections, this is not explicitly written for all parameters, but is always indicated by the open sum which starts with the constant and the interest rate.

In order to fit the model, a single equation is needed again and can in this case be formulated as:

$$S_A = \max\left[0, aA_A + b\left\{1 + \min\left(0, -\beta\left(\tilde{A}_B - A_B\right)\right)\right\}\right] \tag{4.9}$$

Note that the intercept of the actual curve in Figure 4.6 changes marginally for high availabilities (above 1.1) in country B (e.g. $S_A(1.5,1.5) < S_A(1.5,1.1)$). Therefore, this equation is only an approximation, but sufficient enough for the purpose of this study.

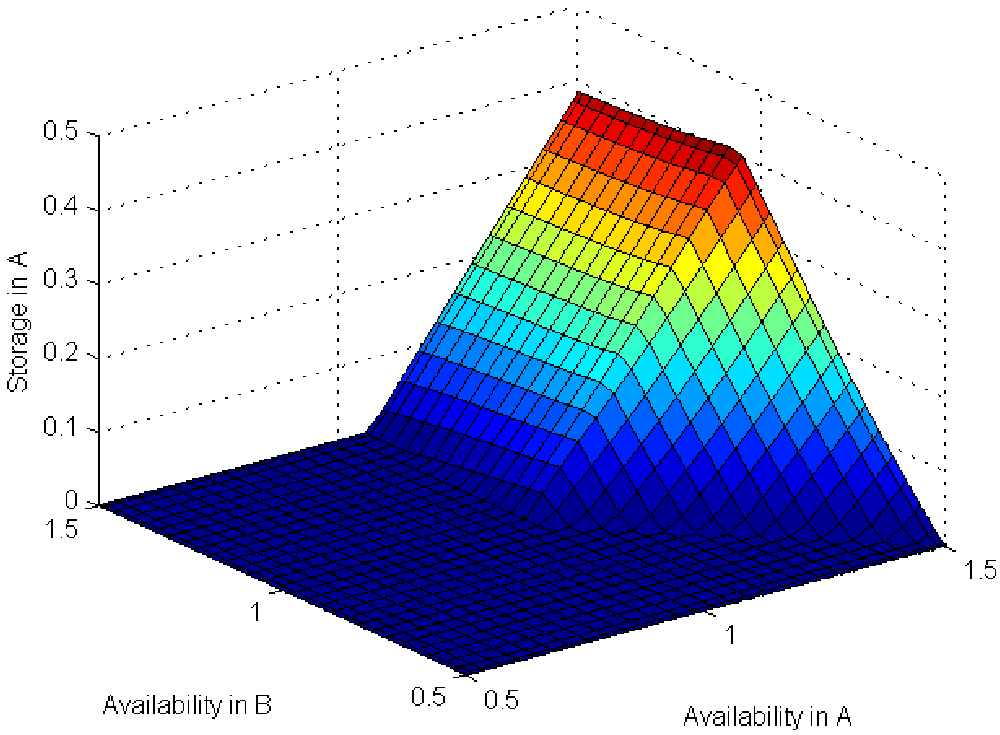

Figure 4.6: Storage in A dependent on availability in A and in B

Notes: Own illustration. Simulation for the two country model without income shocks. Storages takes place only in regions of excess supply. Availabilities and storage can be interpreted as share of the expected harvest.

4.5.3 One country with income shocks

In the case of one country with income shocks but without trade, there are again two state variables, namely the availability and the income level which may both influence stocks. Figure 4.7 shows how the storage rule changes depending on the availability and income for a fixed set of parameters. The graph indicates that income shocks do not influence the slope coefficient of the storage rule but only the intercept, i.e. the threshold. An additional analysis where the slopes were computed and compared confirmed this assumption. Therefore, the results show that the storage rule can be described by the following equation:

$$S_A(A_A, Y) = \begin{cases} 0 & \text{if } A_A < \tilde{A}_A(Y) \\ (a + \omega Y)A_A + b + \rho Y & \text{if } A_A \geq \tilde{A}_A(Y) \end{cases} \tag{4.10}$$

with $\omega = \omega_0 + \omega_r r + \cdots$, $\rho = \rho_0 + \rho_r r + \cdots$, and $\tilde{A}_A(Y) = \rho Y$.

The single equation which could be used to fit the model can be described as:

$$S_A = \max[0, (a + \omega Y)A_A + b + \rho Y] \tag{4.11}$$

As mentioned above, income only influences the intercept which implies $\omega = 0$.

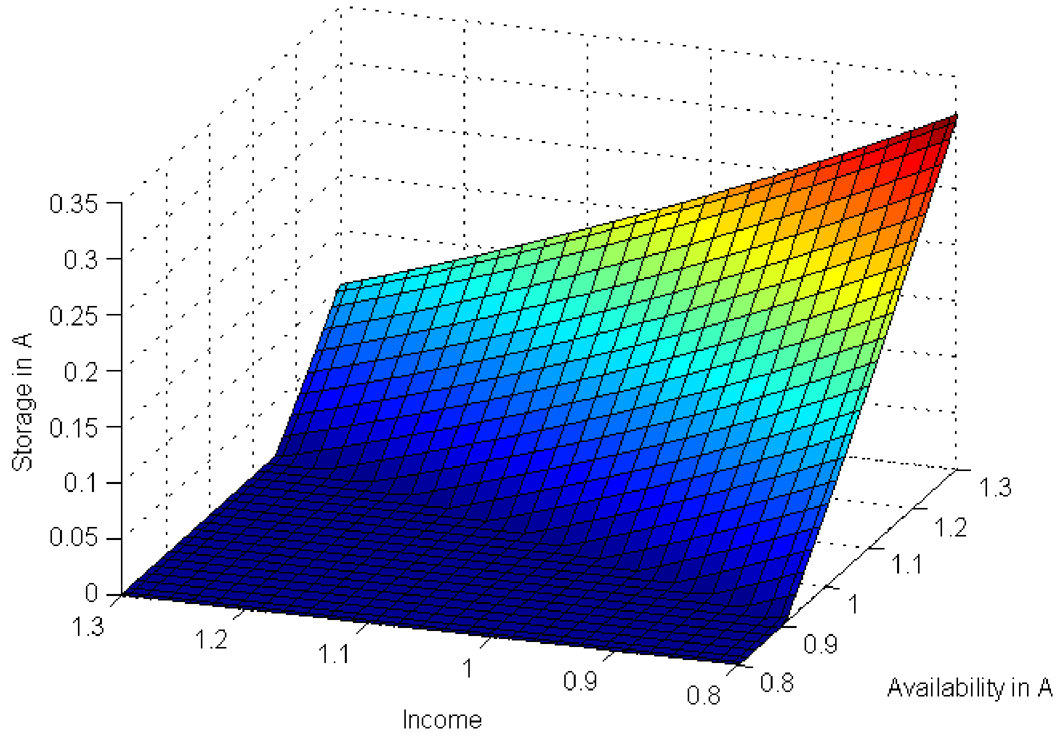

Figure 4.7: Storage in A dependent on the availability and the income level in A

Notes: Own illustration. The income only influences the storage threshold but not the slope.

4.5.4 Two countries with income shocks in country A

Finally, the full model for two countries with income shocks in country A is set up. As there are three state variables now, the results cannot be plotted as in the other cases. But the previous chapters have shown how the different parameters may influence the storage rule. Combing the previous results, the reduced-form approximation of the storage rule can be formulated as:

$$S_A(A_A, A_B, Y) = \begin{cases} 0 & \text{if } A_A < \tilde{z}(A_B, Y) \\ (a + \omega Y)A_A \; + (b + \rho Y\,)\big(1 + \tilde{z}(A_B, Y) - \tilde{A}_A(Y)\big) & \text{if } A_A \geq \tilde{z}(A_B, Y) \end{cases} \quad (4.12)$$

$$\text{with} \quad \tilde{z}(A_B, Y) = \begin{cases} \tilde{A}_A(Y) & \text{if } A_B > \tilde{A}_B(Y) \\ \tilde{A}_A(Y) - \beta\big(\tilde{A}_B(Y) - A_B\big) & \text{if } A_B \leq \tilde{A}_B(Y) \end{cases}$$

and $\tilde{A}_B(Y) = \theta + \tau Y = \theta_0 + \theta_r r + \cdots + (\tau_0 + \tau_r r + \cdots)Y$. This implies that $\tilde{A}_B(Y)$ can be expressed as a linear function with an intercept θ and a slope τ which both are linearly dependent on the model parameters. The parameter τ determines the change of the threshold level for stock-outs under GDP shocks. $\tilde{A}_A(Y)$ could be defined but will cancel out anyway.

In order to estimate the model with non-linear least squares, a single equation is needed. Transforming equation (4.12), the following single reduced-form storage rule approximation can be derived:

$$S_A = \max\big[0, (a + \omega Y)A_A + (b + \rho Y)\{1 + \min\big(0, -\beta(\theta + \tau Y - A_B)\big)\}\big]\,. \quad (4.13)$$

This equation is an important finding of this study which will be used for the subsequent analyses to fit the theoretical model and derive the expected signs of the empirical model. As before, ω is equal to zero thereby slightly reducing the complexity of the equation.

4.6 Testing the reduced-form storage rule approximation

Equation (4.13) is the reduced-form approximation of the storage rule for the case of two countries with one of them suffering from income shocks. The previous sections showed mostly qualitatively why this specific form is chosen and why it is expected to describe the simulation results as a reduced-form equation. The next step is to quantitatively evaluate how good this approximation performs for the CSM. The simulation results from the theoretical model will be used to estimate the parameters of the model described by equation (4.13). Using a non-linear least squared estimation, the goodness-of-fit based on the R-squared is assessed. This is a so-called response surface methodology which relates the response variable (stocks) to the explanatory variables (input parameters and state variables). More precisely, the pre-defined reduced form is fitted for the response variable (stocks) dependent on the endogenous variables which are the input parameters and state variables such that the corresponding coefficients can be estimated econometrically.

A two-step procedure is applied here. In the first step, it is shown that for each set of input parameters individually, the model is able to describe the functional form of the storage rule on the $9 \cdot 9 \cdot 9$ state variable space. Then, the input parameters are the same for each individual grid point of the state variables on which the model is solved. Thus, only the intercepts are included in the regression, i.e. $a_0, b_0, \theta_0, \rho_0, \tau_0, \beta_0$. The grid size was chosen to provide a compromise between the precision of the results, the number of additional parameters which can be included, and the computation time for solving the model. To ensure that income only influences the threshold and not the slope of the storage rule, the estimations were also conducted with ω included but, as expected, it turned out to be insignificant and close to zero. For each of the 162 sets of parameters the model was fitted individually and the R^2 was calculated. The mean of the obtained R^2 was .99972 with a standard deviation of .00004 and a minimum value of .99962, indicating an extremely high fit (Table 4.2; further summary statistics are provided). This indicates that the functional form is an excellent approximation given a specific set of parameters. Furthermore, for the very different structural parameter sets, most of the estimated reduced-form parameters change only slightly as indicated by the coefficient of variation (CV) in Table 4.2. The only exceptions are the parameters ρ_0 and τ_0.

In the second step, the assumption of a linear influence of the different parameters is tested; i.e. whether the dependence on the different parameters (interest rate, demand and supply elasticities, SD of production shocks, and the relative country size) can be captured by linear combinations of structural parameters (i.e. $a = a_0 + a_r r_A + a_\mu 1/\mu_A + a_\alpha \alpha_A + a_\gamma \gamma_A + a_\sigma \sigma_A$) in equation (4.13). Therefore, all the simulation results, i.e. the results for all different sets of parameters, are pooled together. Then the regression is conducted again, this time including the full specification with linear combinations for $a, b, \beta, \theta, \rho$, and τ instead of including only the intercepts. The results (Table 4.3) have six implications: (1) The very high R^2 of 0.9997 indicates that the model is well specified and the equation (4.13) is indeed a very good reduced-form approximation of the storage rule which results from the partial equilibrium model that lacks any a priori closed form solution. (2) Most of the parameters are highly significant, i.e. even significant at the 0.1% level which is partly attributable to the high number of observations. (3) The parameters for the interest rate are all insignificant. However, this conclusion is preliminary as a higher variation of the interest rate might yield different results. (4) The few other insignificant parameters are $\rho_0, \rho_\mu, \rho_\alpha, \tau_0$, and τ_{mu}. (5) All significant parameters are relevant, i.e. (mostly far) above 0.00186 which is not small regarding the model calibration. (6) Most insignificant parameters are small, i.e. (mostly clearly) below 0.00128. From these results, the expected signs of the regression results in the empirical part of the analysis can be deducted.

Table 4.2: Summary statistics of separate storage estimations (first-step validation).

Variable	Mean	Std. Dev.	CV	Min	Max
R^2	0.9997	0.0000	0.0000	0.9996	0.9998
a	0.7855	0.0105	0.0134	0.7637	0.8054
b	-1.0145	0.0465	-0.0458	-1.1007	-0.9384
ρ	0.0009	0.0065	7.6105	-0.0080	0.0158
β	-0.7767	0.0273	-0.0351	-0.8194	-0.7344
θ	0.7519	0.0527	0.0701	0.6760	0.8148
τ	0.0567	0.0424	0.7486	0.0064	0.1184

Notes: Own illustration. Each column shows the summary statistics over the goodness-of-fit (R^2) and the estimated reduced-model parameters using equation (4.13) for each structural parameter set separately. A non-linear least squares fitting procedure is used.

Overall, it is therefore concluded that the piece-wise linear approximation performs very well over the broad set of tested parameters. As explained (the first step of the two-step procedure), it approximates the storage rule well for each individual set of parameters (i.e. only dependent on state variables) which can be seen by the very high mean R^2 of .99972 with a standard deviation of .00004 (Table 4.2). Furthermore, the piece-wise linear approximation is also able to describe the influence of the different parameters on the private carry-over stocks as is indicated by the very high total R^2 of 0.9997 (Table 4.3, the second-step of the procedure). Thus, the pre-defined specific form of the storage equation, combined with the estimated coefficients (Table 4.3) is able to explain almost all the variation in the stock data. Newbery and Stiglitz (1982 chapter 30.2) have provided a piece-wise linear approximation for a very specific set of parameters for a single country without income shocks, i.e. only considering parameters a and b. Their result is however in line with findings in this study, as they provide a range of 0.51 to 0.82 for a (depending on the availability) and -0.54 to -0.94 for b. Here, the result for a fits very well. The result for b is lower but very comparable because the interaction variables β and θ are included in the b provided by Newbery and Stiglitz (1982 chapter 30.2).

Table 4.3: Regression results for collective storage estimation (second-step validation)

	Coefficient	Std. Err.	t-value	P>|t|
a_0	0.7623	0.0005	1538.21	0.000
a_r	0.0000	0.0023	0.00	0.999
a_μ	0.1045	0.0011	94.58	0.000
a_α	0.0253	0.0009	27.93	0.000
a_σ	-0.0921	0.0022	-42.04	0.000
a_γ	0.0236	0.0012	19.06	0.000
b_0	-5.3433	0.0144	-372.29	0.000
b_r	0.0001	0.0744	0.00	0.999
b_μ	-1.9393	0.0379	-51.11	0.000
b_α	0.0641	0.0300	2.13	0.033
b_σ	0.9195	0.0727	12.64	0.000
b_γ	-1.7322	0.0418	-41.46	0.000
ρ_0	0.0013	0.0156	0.08	0.935
ρ_r	-0.0001	0.0710	0.00	0.999
ρ_μ	-0.0212	0.0350	-0.61	0.545
ρ_α	-0.0470	0.0286	-1.64	0.100
ρ_σ	-0.2953	0.0693	-4.26	0.000
ρ_γ	0.5663	0.0390	14.52	0.000
β_0	-0.1412	0.0000	-2857.43	0.000
β_r	0.0000	0.0003	0.00	1.000
β_μ	0.0245	0.0002	116.76	0.000
β_α	-0.0040	0.0001	-32.78	0.000
β_σ	0.0019	0.0003	6.41	0.000
β_γ	0.0225	0.0002	92.80	0.000
θ_0	-4.9728	.	.	.
θ_r	0.0000	0.0206	0.00	1.000
θ_μ	-1.4286	0.0146	-98.02	0.000
θ_α	0.2420	0.0085	28.39	0.000
θ_σ	-0.3438	0.0204	-16.86	0.000
θ_γ	-1.4645	0.0152	-96.04	0.000
τ_0	0.0003	0.0023	0.12	0.903
τ_r	0.0000	0.0104	0.00	0.999
τ_μ	-0.0062	0.0051	-1.22	0.223
τ_α	-0.0159	0.0042	-3.81	0.000
τ_σ	-0.0392	0.0101	-3.87	0.000
τ_γ	0.5933	0.0057	103.75	0.000

Notes: Own illustration. N=118098. R^2=0.9997. Non-linear least squares are applied.

4.7 Empirical estimation

4.7.1 Data description

For the empirical validation of the model, the USDA data for stocks, production and demand from 1975 to 2013 for corn, rice, wheat, soy, and sorghum is used. The data is further complemented with stock data from FAO GIEWS which provides in total 32 countries (after cleaning as described in section 4.7.2). GDP per capita is obtained from the World Bank. The stock and production data is de-trended using the consumption trend from Hodrick-Prescott filtering. Hence, domestic and rest-of-the world (ROW) stocks as well as supply (production plus carry-over stocks) are divided by the long-term consumption trend which produces a stationary series that is also of similar magnitude among different countries. Likewise, GDP per capita in real terms is de-trended using the Hodrick-Prescott filter to obtain a series for income-induced demand shocks. The standard deviation of supply shocks σ_A is calculated as the standard deviation of the cyclical components of the Hodrick-Prescott filtered production data. The scaling parameter for country size γ_A is obtained by dividing the domestic consumption trend by the consumption trend of RoW.

4.7.2 Differentiation between total, public, and private stocks

The stock data from the USDA and FAO GIEWS does not differentiate between public and private stocks. Instead, only their sums, i.e. the total stocks, are reported. Yet, the presented method only works well in the absence of (substantial) public interventions. Hence, three measures are undertaken to ensure that public stocks do not distort the results.

First, only those countries were included, which do not have a substantial public stock such that the total stocks mostly refer to the private stocks. Hence, the included countries are Argentina, Australia, Canada, Chile, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Ireland, Israel, Italy, Japan, South Korea, Netherlands, New Zealand, Norway, Poland, Portugal, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom and the United States. For the post-Soviet countries, only data after 1991 was considered. These countries are currently all high-income OECD member countries, except for Argentina, Chile, Croatia, Hong Kong, and Singapore, all of which are however considered to be high-income economies by the World Bank. This selection ensures that there are only small public stocks which are rarely used and therefore do not influence the results (much).

Second, one has to consider how public stocks and policies may impact private stocks. If public stocks are kept constant during the considered time period (e.g. as strict emergency reserves which remained unused), they do not impact the results. The same holds if public stocks follow the same (profit-maximizing) dynamics as private stocks; however, this is unusual. There is very little empirical evidence on the interactions between public and private stocks. Indonesia's public rice stocks have been reported to not have a substantial impact on private stocks (Islam and Thomas 1996; Timmer 1996). Similarly, the public stockholding program in Ghana has been reported to not significantly influence private stockholder activities (Kornher 2015). However, an empirical quantification of the crowding out effect does not exist for any country. The first attempt to quantify the crowding out effect is presented in chapter 5. There, for the case study of India it is found that every ton of public stocks crowds out half a ton of private stocks. Nevertheless, private storage activities following a profit-maximization approach are found to persist. In this case, the huge involvement of the government would distort the results if it is not explicitly accounted for as in chapter 5. Yet, the dynamics of private profit-maximizing stockholders would still be found, just with changed coefficients. For example, the response of the stocks to the availability would be much lower. In Ethiopia, it has also been reported that private storage activities are very low, partly due to weak storage infrastructure (Gabre-Madhin 2001; Getnet et al. 2005). However, none of the countries involved in the analysis has any large stockholding program or other market interventions which could be compared to India or Ethiopia. The interventions are actually even smaller than the ones in Indonesia and Ghana where no substantial crowding out was found. Therefore, the extent to which the public stocks influence the results is expected to be minimal. Furthermore, in all the countries included in the analysis, private stockholders are expected to have access to credit and up-to-date information, to be able to use relatively modern warehouses, and to not be substantially hindered by governmental regulation.

Theoretical estimations of the crowding out effect exist for various schemes of public stocks. Based on the results from chapter 3, it is possible to make a rough estimation to which extent public stocks could impact private stocks. However, this estimation is limited to the specific scheme of the reserve from chapter 3. Figure 3.4 illustrates how a public reserve impacts private storage depending on the size of the public reserve in the intervention/trigger price. It turns out that as long as the interventions are not too frequent, i.e. the trigger price is high enough, the impact of public stocks on private stocks are small. For example, a trigger price of 40% above the average price would decrease the mean private stocks only by about 4% (the stock level is reduced from 1.45% to 1.4% of the average harvest). Similarly, private stocks would be reduced by about 8% if the trigger price were chosen to be 30% above the average price. In developed countries where consumers are not immediately at risk if food prices increase, it is unlikely that governments would intervene if grain prices increased by 30% above the trend.

The third measure to evaluate to which extent public stocks can distort the result is a simple illustration of how public stocks may follow a similar pattern as private stocks. Therefore, the dependency of the stocks on the total availability is plotted for selected countries which allows visually evaluating the overlap with the theoretical results (Figure 4.8 and Figure 4.9). India and China are illustrated even though they are not considered in the actual analysis due to their large public stockholding programs. In most cases, a nearly linear dependency can be observed for all crops. However, there is some noise (i.e. fluctuations) and sometimes stock levels on the world level are far too low. The kink, i.e. the threshold, cannot clearly be identified in the figures. For the US (Figure 4.9), the slope and the intercept is very crop specific and the linearity is more visible for wheat and corn than for rice. In India, strong noise renders the stocks much more arbitrary but the general dependency still remains visible. This strong noise seems to be a result of the market interventions by the Indian government. The huge government stocks in India have been found to be mainly driven by the Indian minimum support price and only secondary by the total availability (see chapter 5). In contrast, the stocks in China seem to follow to a substantial extent the pattern of private profit-maximizing stocks as the dots for all crops in Figure 4.8 form straight lines with little noise. This is supported by the observation that substantial amounts were released from China’s public stocks during the world food crisis (Yang et al. 2008). Yet, China’s stocks are higher than private inventories would be. In contrast, India’s public stock levels increased during the crisis (compare with chapter 5). Nonetheless, one has to consider that USDA stock estimates for China are vague as the government does not share data on their public stocks. Yet, at least in China where most stocks are public, these stocks seem to follow a somewhat similar dynamic as private stocks, even though the absolute stock levels are much higher[17].

Overall, it can be concluded that the public stocks should not have a significant impact on the results of this study. First, only countries with very low public stock levels are included. Second, the evidence from Indonesia and Ghana and the theoretical evidence from chapter 3 indicate that even substantial public stocks do not necessarily have a significant impact on private stocks. Third, public stocks sometimes follow a somewhat similar dynamic as private stocks as the simple illustration exercise for China indicated. Hence, the results of this study are not expected to be distorted by the minor prevailing interventions in the considered countries.

4.7.3 The non-depletion of empirical stocks

In theoretical studies, stocks are depleted more or less frequently. However, this is not found in empirical data (compare also Figure 4.8 and Figure 4.9). Different explanations have been provided for why empirical stock levels usually never fall down to zero. The first was the concept of a convenience yield which attributes an intrinsic value to the possession of stocks

[17] In all of the scatter plots, important covariates such as income and global supply shocks are omitted which leads to deviations from the piece-wise linear stocking rule over domestic supply. Only the econometric estimations can fully capture the influence of all variables and therefore provide a comprehensive picture of the extent to which the stocks in a certain country can be modelled by the presented method. For China, it also cannot be fully ruled out that the nearly-linear behavior is a result of the method which the USDA applies to estimate the stocks.

(Brennen 1958; Working 1949). This concept was then challenged and complemented with the explanations of mismeasurement and aggregation issues (Benirschka and Binkley 1995; Brennan et al. 1997). Another explanation has been provided by arguing that stockholders follow different motives such as preventing interruptions of production processes or material flows (Carter and Giha 2007). However, these views have also been challenged and new support for the convenience yield have been found (Franken et al. 2009). Operational stocks, which could be a result of different stockholding motives or of a convenience yield, can easily be incorporated by an additive term to the entire storage equation. This is conducted in section 4.7.5. The underlying assumption is that operational stocks, such as the stocks which are required to keep production processes running and therefore maintain a certain flow of products, can be approximated by a fixed share of grain use.

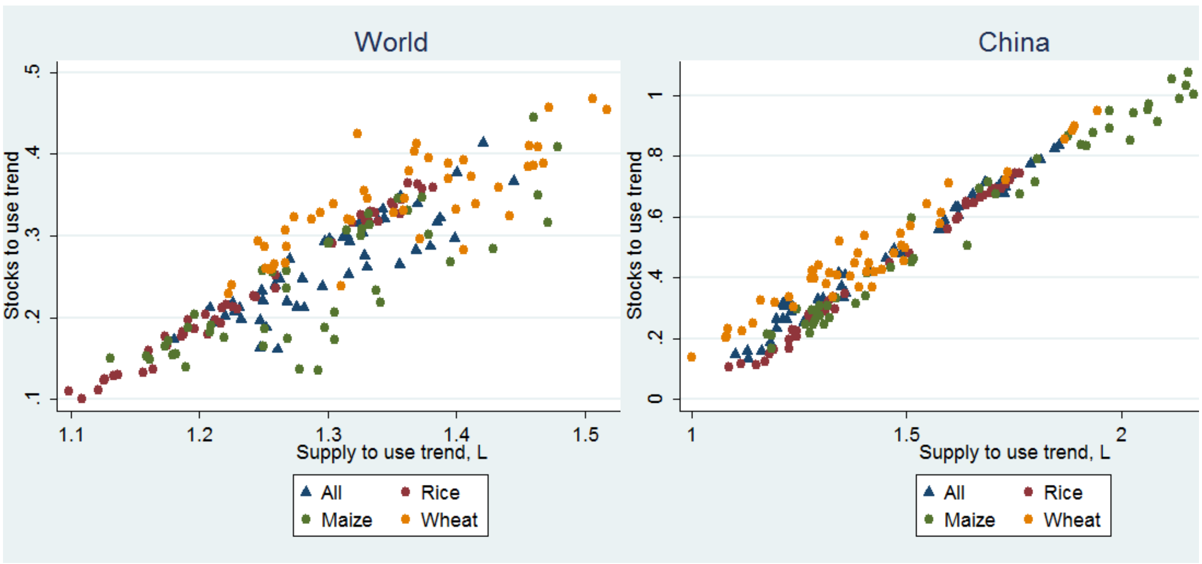

Figure 4.8: Stocks to use trend for stocks worldwide and in China (Own illustration)

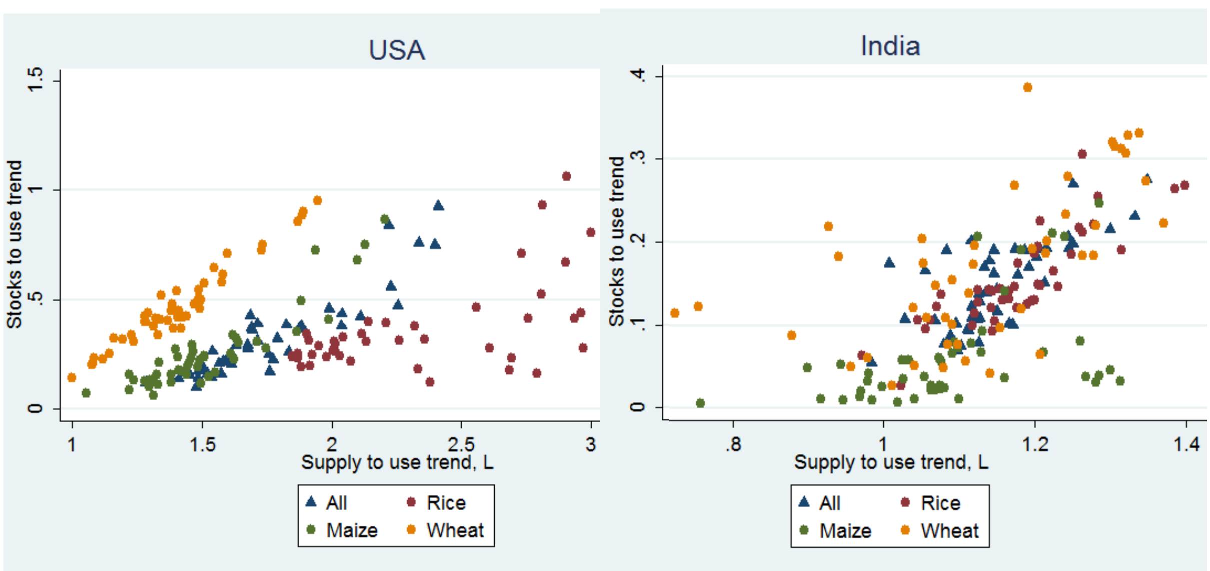

Figure 4.9: Stocks to use trend stocks in the US and in India (Own illustration)

4.7.4 Regression on empirical stock data

To incorporate relevant covariates, a non-linear least square regression on the closing stocks is run based on the approximation equation (4.13). In order to account for potential unobserved heterogeneity, the country and crop-specific mean stocks $\bar{S}_i$ over the considered time horizon are included:

$$S_{i,t} = \max\left[0, \bar{S}_i + aA_{i,t} + \left(b + \rho Y_{i,t}\right)\left\{1 + \min\left(0, -\beta\left(\theta + \tau Y_{i,t} - A_{-i,t}\right)\right)\right\}\right] + \varepsilon_{i,t} \quad (4.14)$$

with $a = \alpha_0 + \alpha_\gamma \gamma + \alpha_\sigma \sigma$ and $b, \rho, \beta, \theta, \tau$ likewise. This gives a fixed-effects-like non-linear panel regression whereas omitting the mean stocks $\bar{S}_i$ yields a random-effects specification. Two different panels are considered: The first uses total grain stocks ("Total Grains" in Table 4.4) and total grain supply as relevant variables, while the second specification uses a panel over countries and additionally over crop types ("Pooled Grains"). The first specification is appropriate if grains are perfect substitutes and only total grains matter for the market equilibrium. The second specification accounts for heterogeneity among grains but misses the substitution effects. The availability of comparable data on some of the structural parameters like the demand and supply elasticity as well as the interest rates is scarce. Therefore, and due to the insignificance of the interest rate in the theoretical model, only the potential impacts of the variation of shocks and the size of the country on the reduced-form parameters are controlled for. A benchmark regression on the dataset generated under section 3.4 on only those variables that are used in the empirical data is also added (column "Theoretical Model" in Table 4.4).

Regression results are shown in Table 4.4. The magnitude of the estimated coefficients from the empirical data and the generated data ("Theoretical Model") are difficult to compare due to scaling issues and therefore these are not of particular interest. Instead, the focus lies on qualitative behavior predicted by the theoretical model and whether this is confirmed by the empirical analysis. The grey shaded cells indicate where the empirical model matches the theoretical results. This is the case if either both coefficients are insignificant or if the sign of the coefficients from the empirical model matches the one from the theoretical model in case both coefficients are significant. Most importantly, the slope coefficient a_0 is positive and significant in all specifications, indicating that high supply leads to higher stock-to-use ratios. This effect is stronger for larger countries than for smaller ones, indicated by the positive sign of a_γ which holds for all but one specifications and is in line with the results from the theoretical model. On the other hand, the intercept b_γ is smaller for large countries, which is what the theoretical model predicted. Combining both, it implies that larger countries tend to start storing later (i.e. at higher supply levels), but then have a higher slope, i.e. start to build up stocks more quickly. The influence of the standard deviation of shocks on the slope and primary intercept coefficient b is not observable in the empirical data.

Table 4.4: Regression results for the empirical estimation of closing stocks

		FE-like			Random Effects		
		Empirical Model		Theoretical Model	Empirical Model		Theoretical Model
		Total Grains	Pooled Grains		Total Grains	Pooled Grains	
Slope coefficient **α**	a_0	.082**	.119***	.790***	.208***	.237***	.789***
		(.035)	(.022)	(.0002)	(.051)	(.06)	(.0002)
	a_σ	3.8e-06	6.2e-06	-.096***	1.7e-05	1.4e-05	-.091***
		(6.0e-06)	(8.2e-06)	(.002)	(1.6e-05)	(2.0e-05)	(.003)
	a_γ	3.56***	1.99***	.0230***	-1.79	1.83**	.021***
		(1.12)	(.362)	(.001)	(1.98)	(.899)	(.002)
Primary intercept coefficient **b**	b_0	.032	.52	-1.21***	.321	.113**	-.973***
		(.054)	(1.03)	(.001)	(.246)	(.049)	(.001)
	b_σ	1.7e-05	1.9e-03	.197***	-6.2e-05	2.6e-04	.181***
		(3.0e-05)	(3.6e-03)	(.011)	(7.8e-05)	(1.8e-04)	(.017)
	b_γ	-20.8**	-31.4	-.362***	-9.01	-12.1***	-.523***
		(9.84)	(59.2)	(.008)	(8.46)	(3.2)	(.010)
Primary intercept shift due to GDP **ρ**	ρ_0	-.103**	-.75	-.008***	-.454	-.076	-.009***
		(.049)	(1.44)	(.001)	(.269)	(.053)	(.001)
	ρ_σ	-9.8e-05	-3.1e-03	-.00265	5.2e-06	-3.8e-04***	.063***
		(5.8e-05)	(5.7e-03)	(.00948)	(8.6e-05)	(1.4e-04)	(.013)
	ρ_γ	23*	31.9	.102***	16.8*	9.04***	.055***
		(11.7)	(59.8)	(.007)	(9.54)	(2.39)	(.008)
Secondary intercept shift due to trade or GDP **β**	β_0	-.115	-.154	-.645***	3.4e-03**	-.349***	-.805***
		(.)	(.32)	(.0002)	(1.6e-03)	(.094)	(.0003)
	β_σ	-2.6e-06	3.4e-06	-.020***	-9.2e-07**	2.0e-05**	-.082***
		(2.8e-06)	(8.9e-06)	(.002)	(4.1e-07)	(1.0e-05)	(.00563)
	β_γ	1.17**	-.01	.119***	.066*	.417***	.331***
		(.549)	(.019)	(.002)	(.032)	(.154)	(.003)
Secondary intercept shift coefficient **θ**	θ_0	-191	-2.17	.832***	646***	-.152	.833***
		(.)	(12.3)	(.001)	(223)	(1.9)	(.001)
	θ_σ	.014***	-4.3e-04	-.024**	1.48***	2.0e-03***	-.176***
		(5.5e-04)	(3.8e-04)	(.011)	(.371)	(6.2e-04)	(.016)
	θ_γ	-1.1e+03***	5.11**	-.769***	-9.5e+04	-82.6***	-.674***
		(86.2)	(2.26)	(.008)	(.)	(26.3)	(.009)
Secondary intercept shift due to GDP **τ**	τ_0	322	-.992	-.006***	-178	1.68	-.006***
		(.)	(.622)	(.0008)	(121)	(1.61)	(.001)
	τ_σ	-.016***	2.2e-05	.002	-1.34***	-1.8e-03***	.054***
		(9.1e-04)	(4.0e-05)	(.009)	(.422)	(6.0e-04)	(.011)
	τ_γ	907***	-1.64	.605***	7.6e+04***	77.4***	.559***
		(139)	(1.26)	(.006)	(1.1e+04)	(25.5)	(.006)
	R^2	.84	.765	.9997	.855	.755	.9995
	Obs	446	1810	118098	446	1810	118098

Notes: Own illustration. Non-linear least square regression with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered by country and crop in parentheses. Grey shaded cells indicate that the estimated coefficient has the same sign as expected by the theoretical model for which the simulation results were fitted with the same model specification which was used for the empirical data.

For the other parameters, the coefficients of the empirical model are not significant in many cases which may be attributable to partly low data quality or other factors discussed in the next section. However, there are very few cases where the coefficient is significant but the sign is not in line with the theoretical findings. Depending on the specification, many of the GDP-related coefficients are as expected from the theoretical simulations. This indicates that stockholders also consider demand changes in their decision making. Similarly, many of the trade related coefficients are significant and in line with the theoretical findings. This underlines the high degree of market integration in the considered countries and that stockholders make use of the supply and demand situation in other countries. The high R^2s imply that the empirical model is able to reproduce and explain most of the variation in the empirical data.

4.7.5 An alternative minimalistic regression on grain stocks

The somewhat large number of insignificant coefficients in the empirical regression can have several reasons: One explanation can be that real-world storage is distorted by market failures (e.g. high transaction costs) or policy interventions that follow a different logic than the optimal storage model. The inclusion of storage and trade costs, however, accounts to a certain extent for transaction costs. Likewise, the considered countries are chosen to minimize the impact of public stocks and policies. The somewhat large amount of insignificant coefficients and the unexpected sign for some coefficients can also be attributed to the minor changes of slopes and intercepts between countries. Even if they change, these changes may not be attributable to the factors that have been controlled for with real-world data. To consider this possibility, a minimalistic reduced-form storage model is run which excludes the possibility that underlying structural parameters affect slopes and intercepts of the piece-wise linear storage approximation. In contrast, a homogenous response among all countries is assumed, i.e. $a = \alpha_0$, $b = b_0$ etc. in equation (4.14). This approach is comparable to the first-stage model validation in section 4.6 (Table 4.2). Since the parameter ρ is insignificant in the individual regressions in section 4.6 as well as in the full model, many coefficients related to ρ are insignificant (see Table 4.3). Therefore, ρ was omitted in the regression. To further account for working or operational stocks that are contained in the data, the term w was added to the regression. Hence, the resulting regression model reads as

$$S_{i,t} = \max\left[0, \bar{S}_i + aA_{i,t} + b\left\{1 + \min\left(0, -\beta\left(\theta + \tau Y_{i,t} - A_{-i,t}\right)\right)\right\}\right] + w + \varepsilon_{i,t} \qquad (4.15)$$

Regression results are shown in Table 4.5. The first surprising result is that for the generated (stationary) data, i.e. the theoretical model, the fit remains extremely high. This is indicated by the R^2 of 99.1 %. Thus, the reduced-form storage model performs well even when no flexibility of intercepts and slopes is allowed, indicating a very limited influence of these parameters on the model's general form. In contrast to the full regression in Table 4.4, the signs of the coefficients are now fully in line with expectations of the theoretical model. Only in case of θ, which determines the change of the constant threshold shift for stock-outs under GDP shocks and supply shocks abroad, the regression on real-world stock data yields a statistically insignificant coefficient.

Table 4.5. Regression results for a minimalistic reduced-form closing stocks model

	Empirical Model	Theoretical Model
Slope coefficient a	.354***	.785***
	(7.1e-03)	(.001)
Primary intercept coefficient b	-1.11***	-1.01***
	(.071)	(.001)
Secondary intercept shift due to trade or	-.0003***	-.774***
GDP β	(8e-05)	(.001)
Secondary intercept shift coefficient θ	-4100	.748***
	(.)	(.001)
Secondary intercept shift due to GDP τ	3100***	.058***
	(330)	(.001)
Working stocks w	.197***	
	(.006)	
R^2	.692	.991
Observations	1810	118098

Notes: Own illustration. Non-linear least square regression. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. The empirical model is applied to pooled grains. All independent variables are de-trended as described before.

The statistically significant a and β in the empirical model indicate a high level of market integration: Domestic storage responds strongly to domestic supply as the slope coefficient a is positive, significant, and high. However, it is not as high as expected from the theoretical model. Additionally, domestic storage also responds to international supply as the slope coefficient for the international supply, β, is also significant. It is negative due to the way it is defined (compare equation (4.15)). Finally, operational or working stocks w are estimated to be slightly below 19.7% of domestic consumption which appears to be relatively high but still reasonable considering that it contains stocks at all levels of the value chain. These operational stocks describe the stocks which are kept every year to keep the flow of products and operations running. The parameters α and β differ significantly from one another between the theoretical and empirical model, even though they both have the same sign. As a and b are smaller than expected, it seems that real-word stocks do not quite respond to the supply situation as expected. Instead, it seems that stocks start to pile up only if the supply is substantially above the expectations. Otherwise, stocks remain at a minimal level. Furthermore, once this threshold is passed, empirical stocks seem to increase somewhat slower than predicted by the theory (as a is lower in the empirical model). Overall, this behavior could indicate that stockholders are somewhat risk averse. Instead, it may also be a result of policy disturbances, even though the considered counties do not have a large degree of government interventions. However, both hypotheses require more evidence and alternative explanations may be more appropriate.

4.8 Conclusion

Numerical modelling of private speculative storage nowadays usually relies on the competitive storage model (CSM), potentially including extensions such as a convenience yield or uncertainty about the state of the system. However, prevailing shortcomings include (1) the complex numerical implementation which limits the dimensionality of the model, usually reducing it to one or two countries and one or two policies; (2) the lack of considering actual stock levels in empirical validation exercises; (3) empirical stock determinants can only be quantified indirectly through iterative adjustments of model parameters as no analytical solution of the model exists. Alternative models directly quantifying impacts lack a solid theoretical foundation. The approach presented in this study allows addressing these issues by providing a piece-wise linear reduced-form equation which can describe private profit-maximizing stockholding for a broad set of parameters and model assumptions. It offers an alternative empirical validation approach which for the first time considers actual stock levels, allows direct empirical testing of individual stock determinants and is applicable to high-dimensional modelling exercises.

In contrast to many econometric analyses, this study does not make any a priori assumptions about the underlying mathematical relationships between variables. Instead, a theoretically founded reduced-form approximation of the numerical storage rule is derived by using the CSM in a general setting with trade, GDP shocks and large parameter variations. This approximation is extremely flexible and precise when estimated with the stock data generated from the theoretical model. It is therefore a useful approximation for storage behavior in future empirical and applied research. This way, the need to solve the CSM is overcome and thereby the complexity is reduced without reducing its precision as long as the model assumptions hold.

The qualitative behavior of private grain stockholders which results from the model is in accordance with the empirical findings and can be summarized as follows: Ending stocks are zero if both domestic and global supplies are below a certain threshold. This threshold is shifted downward by positive GDP shocks, i.e. positive income shocks lead more likely to stock outs. If production in the rest of the world falls short, both the threshold and the slope change and the crop is exported instead of being stored. The threshold and slope are influenced by structural model parameters, in particular, storage costs, interest rates, supply and demand elasticities as well as the variability of domestic harvest shocks and harvest shocks in the rest of the world. If supply within the country and the rest of the world is above the critical threshold, ending stocks depend positively and linearly on domestic and global supply. The slope is again influenced by structural model parameters.

Applying the reduced-form model to observed production, stock and income panel data for 32 countries and five crops confirmed the appropriateness of the reduced-form approach. Due to the piece-wise linear storage rule, a non-linear least squared regression was used. The estimated coefficients are largely in line with those expected (i.e. significant and with the same sign as in the regression with data generated by the theoretical benchmark model). Structural characteristics of countries and crops, however, seem to have only a small impact on threshold levels and slopes.

Three results are of direct policy relevance: First, operational stocks throughout the value chain are roughly 19.7% of domestic consumption, implying that stock-to-use ratios have to be subtracted by 19.7 percentage points to yield the amount of stocks that are actually available for consumption smoothing. This emphasizes the importance of observing stock-to-use ratios when tracking potential supply shortfalls. Second, domestic stocks respond strongly to the international supply situation which suggests a high degree of market integration. This underlies the need for multinational agreements and regulations about how to deal with supply shocks in individual countries as well as at the global level. Third, GDP shocks are important in the theoretical and the empirical model thereby indicating that stockholders do also anticipate future demand. This highlights the need to focus also on demand side factors rather than only supply side factors in information systems like AMIS (compare chapter 2) such that stockholders and other market actors can easily make good estimations about the future demand.

Similarly to chapter 3, the main limitations arise from the model setup and the parametrization. Interactions with other sectors of the economy are not captured and certain restrictions on the behavior of individual agents are imposed, e.g. assuming private stockholders maximize profits. Furthermore, the model assumes complete markets and stationary parameters. The quality of stock data is generally low (compare chapter 2) which might further limit the results.

Future research should explore the impacts of domestic stabilization policies on private storage in empirical data. This study has made an important contribution toward this as it provides a procedure to directly quantify empirical drivers on the basis of a theoretically well-founded model. Chapter 5 provides a first analysis in this direction. In that analysis, the results from this study are used to derive an even simpler version of the storage rule which is then applied to data from India in order to determine drivers of empirical private storage in India. Further research should also focus on the role of policies in leading to higher or lower than optimal (private) grain stocks. In addition, future studies should use the presented method and apply it to individual countries and crops for a full empirical validation of the model which also accounts for public storage, trade distortions, and time-dependent transportation costs.

5 What Drives India's Rice Stocks? Economic Theory and Empirical Evidence[18]

5.1 Abstract

India has a long tradition of maintaining public rice and wheat stocks. Storage and trade policies helped to stabilize prices in the past. However, stock levels and costs are surging while it remains unknown how different factors quantitatively contribute to public stock levels or how private stockholders are affected. This study addresses these issues by developing a new method to empirically quantify drivers of public carry-over rice stocks at the national level. Furthermore, it applies the method developed in chapter 4 and combines it with an instrumental variable approach to quantify determinants of private grain stocks. Public storage is found to be inert and driven by the minimum support price (MSP), market supply, and export bans. Private stocks are driven by private supply (production and private stocks) and export opportunities. Each ton of public stocks crowds out half a ton of private stocks but despite huge government interventions, speculative storage activities persist. This is beneficial for consumers as the public stocks currently offer no crisis-responsive consumer protection – only export restrictions do. The 29% increase of the real minimum support price in 2008 contributed 4.9 million tons to public stocks, the export ban another 2.9. These factors, combined with the bumper harvests in 2010 and 2011, led to the recent surges in public stocks. Findings furthermore indicate that policy makers were aiming to implement price stabilizing policies in the wake of the world food crisis but did not anticipate that these policies would result in massive public stock increases. This underlines the need for adjustments in the current system. Different econometric models are applied as robustness checks and yield comparable results.

5.2 Introduction

Over many years, India's government has tried to tackle two problems with their storage and trade policies: (i) low prices for staple food commodities which may hurt producers, and (ii) high prices which may be problematic for consumers. The rational for public interventions to stabilize prices is provided by the large share of poor people as well as the sensitivity of the population to high prices (compare e.g. Sidhir 2004). The lower boundary for prices is effectively represented by the Minimum Support Price (MSP) which is set by the government every year before planting of the new crop starts. The MSP is designed to cover the costs of production and leave a "reasonable" margin to farmers (Kozicka et al. 2015b). At this price,

[18] The estimation of public stocks (which is the biggest part of this paper) has not been published before. An earlier version of the private storage estimation in this work has been published as a part of the discussion paper Kozicka, M., Kalkuhl, M, Saini, S., and Brockhaus, J., 2015. "Modelling Indian Wheat and Rice Sector Policies". ZEF Discussion Paper 197 as well as ICRIER Working Paper 295. An even earlier version was published with the same title and authors in the conference proceedings of the 2014 AAEA Annual Meeting, Minneapolis.

open-end procurement of rice paddy is guaranteed to farmers. It was claimed, that the MSP follows the international prices in the long run, but even then it remains exogenous for the Indian market actors. Grains are then stored and given to the poor at subsidized rates. However, farmers are free to sell their grains to the open market, i.e. any type of market agent, instead. Trade quotas and bans are used as ad-hoc policies to prevent price surges. While this stabilized domestic prices (Anderson et al. 2013; World Bank 2010), it also amplified world price increases (Anderson et al. 2013; Headey 2010) and led to surging public stocks resulting in large fiscal costs for the government (Kozicka et al. 2015b). Hence, it is questionable whether India's price stabilization policies are cost-effective and can be sustained in the long run. Given the large share of poor households in India, pro-poor food policies are of crucial importance for the country but new policies which achieve the same goals at lower fiscal costs and with lower levels of leakages need to be explored (Kozicka et al. 2015a). Whether less government involvement and more reliance on the private sector can be part of such a strategy is a question of particular importance.

This study explores the drivers of public and private carry-over rice stocks under the current institutional setting. A new method is developed to analyze the drivers of public storage and a recently developed theoretical method for the analysis of private stock drivers based on the competitive storage model (chapter 4) is used, adjusted, and applied to Indian data and policies. This allows endogeneity problems to be overcome, which typically plague empirical modeling of supply, demand, and storage. In particular, it is analyzed how the market supply, export opportunities, and policy variables such as buffer norms and the MSP influence the carry-over rice stocks. Public stocks can be analyzed with a simple OLS regression on the levels or first differences while private rice stocks require an instrumental variable approach. To deal with the relatively low number of observations, models are kept as simple as possible and results for different specifications are provided (including levels and first difference specifications). Additionally, different estimators are used in case of the instrumental variable approach to estimate private stocks. Finally, both USDA and FAO-AMIS data is used for separate private stock regressions as an additional robustness check. The Indian government itself does not provide any estimates for private stock data. Overall, this study therefore contributes to the string of literature which analyzes India's market interventions to improve food security policies and possible options for reforms of these policies (Baylis et al. 2013; e.g. Ganesh-Kumar et al. 2012; Gouel et al. 2014; Gulati and Jain 2013; Gulati and Saini 2014; Gupta 2013; Jha et al. 2007; Kozicka et al. 2015b; Pursell 2014; Shreedhar et al. 2012; Srinivasan and Jha 2001, 1999).

A particular focus of this study is the interaction between public and private stocks. In general, knowledge about how public stocks influence private stocks is mostly derived from theoretical models (compare chapter 3 and Miranda and Glauber 1993; Williams and Wright 1991; Wright and Williams 1982) but quantitative empirical studies on this question are missing. Typically, stock data is not available or is poorly documented (Abbott 2013). India constitutes an exceptional case in the sense that data on both private and public stocks is available and the system underwent no major changes for a time period of about 40 years. Hence, India provides a rare situation that allows analyzing how public stocks influence private stocks. Naturally, results are specific to India. Private stocks are held by farmers, traders, millers, and co-operatives. Private-public partnerships have also been built to extend and modernize the storage capacity (World Bank 2011).

Public rice stockpiling policies are well defined in India by setting the MSP which drives the procurement. In addition, rice millers are indirectly taxed by having to deliver a state-dependent share of their milled rice to government agencies (Saini and Kozicka 2014). This so-called levy has been used since the mid-1960s (Acharya et al. 2012) but it has been announced to be discontinued from October 2015 onward (Dash 2015). The procured grains are stored and (supposedly) given to the poor through the public distribution system (PDS) which offers predefined quantities of rice and wheat at fixed prices. However, leakages are substantial (Drèze and Khera 2015; Gulati and Saini 2015). Up until 1997/98 the distribution was non-targeted and specified quotas of subsidized grains were distributed through so called fair price shops (Jha et al. 2007). From 1997/98 to 2000/01, a transition to a targeted system was made in order to reduce costs and improve targeting the poor (ibid.). Quantities and prices then became specified for three groups, the poorest of the poor (AAY), the below poverty line (BPL) and above poverty line (APL) (for an analysis of the PDS compare e.g. Khera 2011). These quantities and prices are rarely changed. Other Welfare Schemes (OWS) exist, through which the government releases additional quantities such as for mid-day meal schemes (Saini and Kozicka 2014). In this analysis, these are treated together with the PDS offtakes. Additionally, the government can release grains for public exports or through the Open Market Sales Scheme (OMSS) if stock levels are above the predefined stock norm. In contrast, public imports, which rarely occurred, may be used to ensure stocks do not fall below the norm. Figure 5.1 provides an overview about all processes related to the public carry-over rice stocks, i.e. the inflows and outflows which happen during the marketing year.

Regulatory policies for private storage have been in place in the past and have partly been reenacted such as upper limits on storage volumes for different types of agents. These regulations were introduced by the Essential Commodities Act enacted in 1955. In 2000-2001, rice and other commodities were no longer regulated (Ahluwalia 2002; Landes and Gulati 2004). However, during the world food crisis in 2007-2008, regulations on rice and other food staples were put back in place (Thaindian News 2008). These policies are criticized but still maintained (Cummings et al. 2006; Landes and Gulati 2004; Pursell 2014; Reardon and Minten 2011; Saini and Kozicka 2014). Furthermore, these policies are imposed on the state level, very time-dependent and ad-hoc, poorly documented and difficult if not impossible to aggregate to the national level. Often these policies are not fully implemented or the implementation suffers from corruption and intransparent and lengthy processes (Mooij 1994). All these factors make it impossible to control for impacts of such policies and as a result they are not considered in the analysis.

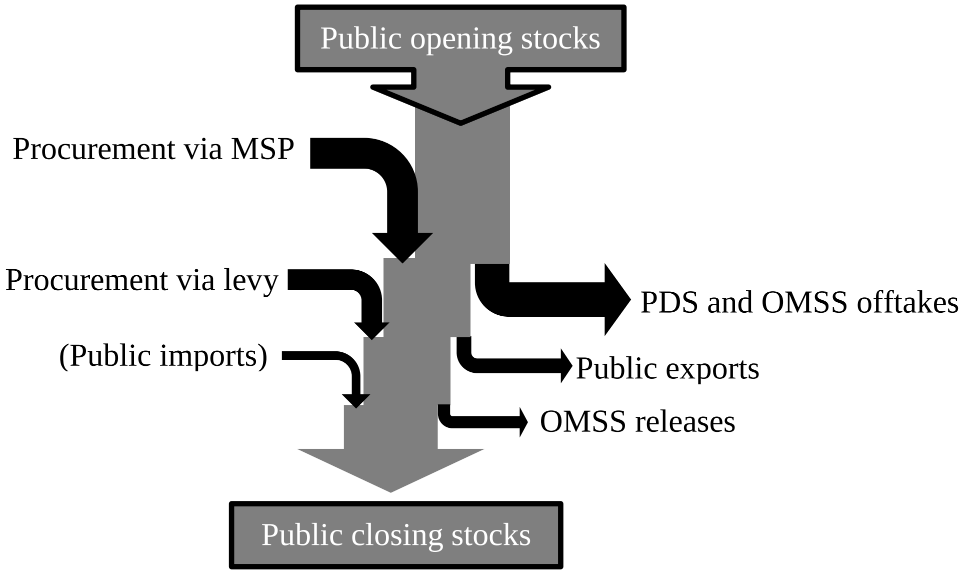

Figure 5.1: Overview of drivers of public ending stocks (inflows and outflows)

Notes: Own illustration. The sizes of the arrows indicate qualitatively the relative importance of the process. Public imports are in brackets because they rarely occurred and if so, they were very small.

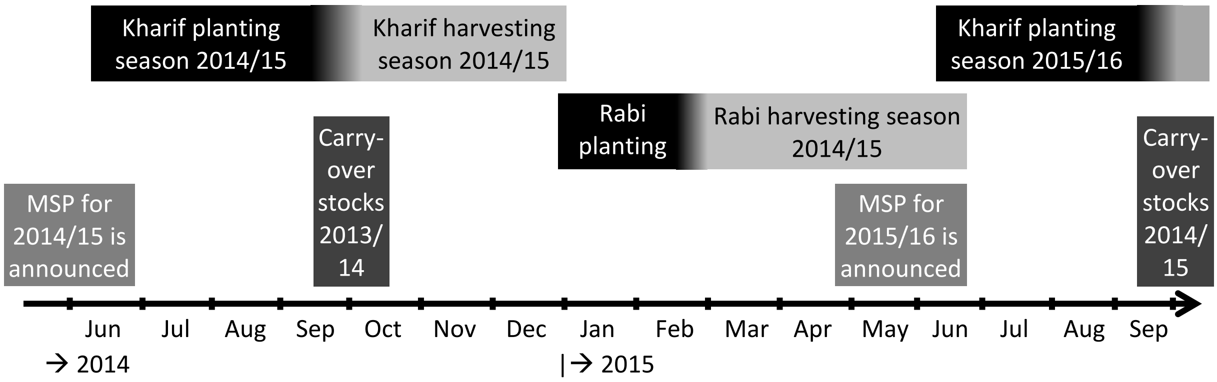

Figure 5.2: Timeline of events within one marketing year (Own illustration)

There are two rice crop seasons in India, the bigger kharif crop is harvested between October and December and the smaller rabi crop is harvested from March to June (Figure 5.2). Thus, stocks reach their lowest levels at the beginning of October, right before the new harvest is starting (Figure 5.3 and Figure 5.5). Hence, this is considered to be the end of the marketing year where the carry-over stocks are measured. The highest public stock levels are observed between March and April when the second harvest is procured. Overall, some modern silos are available but in most areas there is a lack of modern storage facilities and grains are commonly stored with the cover and plinth method which results in huge losses (Sharon et al. 2014).

The following sections successively describe the data, methodological approach, estimation strategies, results, and conclusions.

5.3 Data

Data is collected for as many years as possible; however, the data-generating process must not change during the time of the analysis. Before 1975, there were two official prices announced by the government, the Minimum Support Price (MSP) which was a lower boundary of the rice price and the Procurement Price at which the crop was procured by public agencies (Ramachandran 2005). Usually, the procurement price was higher than the MSP but lower than the market price. In 1975, the system was changed to its current version where there is only one price, the MSP, which is announced and guarantees open-end procurement at this price by the government (ibid.). For this reason, no data for the years before 1975 is considered. As a result, a maximum of forty observations can be obtained with data from 1975 to 2014. During this time period, no major reforms were carried out which changed the overall nature of the data-generating process. The most important reform was the National Food Security Act 2013 (NFSA) which extended the existing public distribution system to provide subsidized grains to about two thirds of India's population. So far, this act has been rolled out only in some states due to several implementation difficulties, including identifying beneficiaries (Das 2015; High Level Committe on Restructuring of the FCI 2015). Therefore, the buffer stock norms were adjusted and accompanied by changes in the public distribution system (Gulati and Saini 2014). However, procurement procedures did not change.

Data on the MSP, public stocks, and buffer norms is obtained from the Food Cooperation of India (FCI), the Ministry of Statistics and Programme Implementation, and the Reserve Bank of India. Production and demand for India as well as for the rest of the world is obtained from the USDA. The MSP is deflated with the World Bank Consumer Price Index. Gulati et al. (2013) provide the times when rice exports were banned.

Empirical data on storage is always scarce and badly documented. The data collection, dissemination and transparency has often been criticized (e.g. Abbott 2013). However, the FCI publishes monthly stock levels for the main staples from 1995 onward. October rice stocks, which are the closing stocks before the new harvest is brought in, are reported from 1990 onward only. However, January (end of the fiscal year) and April stock levels are also reported in the years before and could be obtained from 1972 onward. Data on private storage is usually even harder to obtain. Nevertheless, in India, both the USDA and FAO provide data for the total closing rice stocks, i.e. the sum of private and public stocks in October (FAO-AMIS 2015; Mustard and Singh 2015). It is claimed that no other information is published about privately held rice stocks (Mustard and Singh 2015) and that industry sources are consulted for the USDA estimations. Apart from using industry sources, stock data is often calculated as residual from demand and supply balances (Abbott 2013). The AMIS-website, where the FAO data is obtained, defines the ending stocks as the quantity of the crop held at all levels within the food system before the new crop is harvested (FAO-AMIS 2015). Furthermore, AMIS states that its forecasts are based on official and non-official sources. However, no specific details are provided on how the total stock levels are obtained. FAO STAT only reports stock changes but not stock levels, but a comparison shows that their stock changes do not correspond to the total FAO-AMIS or public FCI stock changes which indicates that other sources or inputs must have been used for the calculation of the total stocks. Often, FAO stock data is computed as a residual from the estimation of the other demand and supply categories such as production, trade, losses, and total demand (Abbott 2013).

Data on surplus of the rest of the world (RoW) is calculated by subtracting the demand trend from the actual production which is brought in at the beginning of the marketing year. The trend is used because demand is not fully foreseeable during the marketing year. Data on production, private stocks, and public stocks is detrended by a Hodrick-Prescott filtered domestic consumption trend to obtain a stationary time series. For the surplus in RoW, the RoW consumption trend is used. Formal tests for stationarity are not reliable without a large number of observations. Nevertheless, most variables are stationary after detrending, according to the augmented Dicky Fuller test, but supply and public stocks are not. Therefore, and as an additional robustness check, results for first difference estimations are reported additionally in the result tables. First differences are stationary for all variables according to the augmented Dicky Fuller test.

5.4 Method to predicting missing observations for public stocks

As explained in the previous section, closing rice stock data is missing in the years before 1990 and for 2015, but January and April stock levels are available for all years and can be used for predicting the October stock levels. There is a large amount of literature about how to deal with missing data (e.g. Afifi and Elashoff 1966; Jones 1980; Little and Rubin 2002; Little 1992). However, the prevailing situation differs in the sense that data on ending stocks, i.e. October stocks, is missing before 1990 and for 2015 but there is data on January and April stocks for those years. Therefore, instead of using maximum likelihood, imputation, Bayes or non-parametric methods, the knowledge of the January and April stock levels can be used to predict the October stocks. It is hence important to notice how stock levels change from April to October (Figure 5.3). The smaller rabi harvest takes place in March and April such that stocks reach their highest levels during this time. Procurement still takes place between April and October, but the decrease from April to October indicates that it plays a minor role during this period. Hence, most of the stock changes are a result of releases. This is confirmed by the procurement data because only 23% of the yearly procurement is processed in the six months from beginning of April to the end of September (yearly average calculated from the 1991 to

2009 FCI procurement data). Gulati and Jain (2013) also find that these six months have the lowest levels of procurement during the year. Additionally, the value for the procurement share has been relatively constant over the years as the standard deviation of the yearly share of procurement within these six months is less than 5% despite a slight increase over the years. The relatively stable procurement between April and October therefore indicates that the storage inflow can be approximated relatively well for the missing years by assuming similar patterns as for the years from 1990 onward where data is available. However, stock releases also need to be approximated in the same manner. The main way to release stocks is through offtakes for the PDS. In comparison, the amount released through OMSS and public exports are small. Gulati and Jain (2013) show that there is hardly any seasonality in rice offtakes. Figure 5.4 presents the monthly rice offtakes from 1999 to 2001 which also show little seasonality and in addition no major differences within these three years. This justifies the assumption that stock releases before 1990 can also approximated by stock releases in later years. This periodic uptake of large stocks and subsequent releases over the marketing year result in large costs for the government and have therefore been criticized (e.g. Shreedhar et al. 2012).

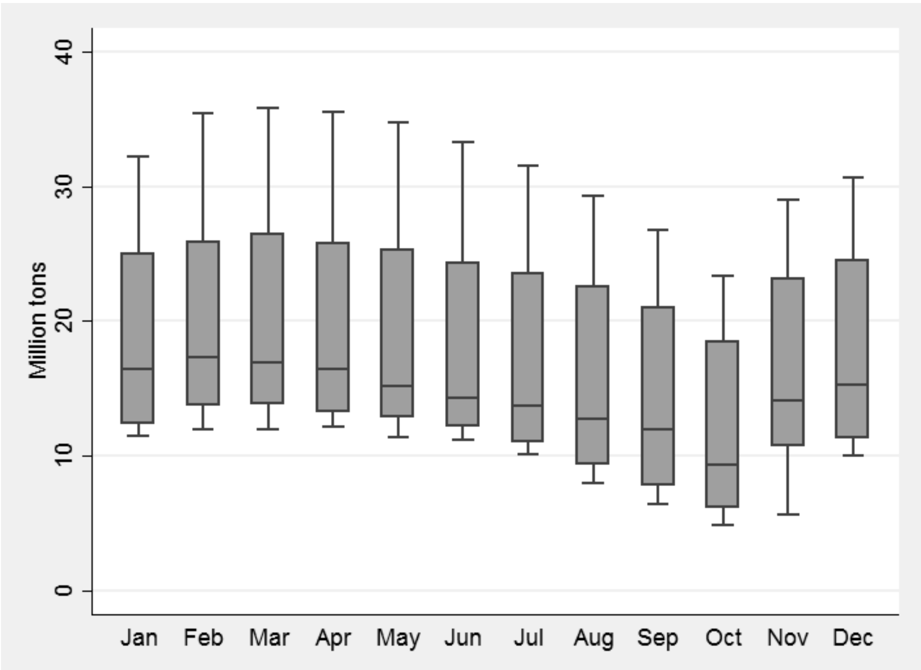

Figure 5.3: Monthly public rice stock levels

Notes: Own illustration. Markers indicate upper limit and lower limits, 25th and 75th percentile and the median. Raw data from January 1995 to September 2014, obtained from FCI.

Figure 5.5 shows the changes of the public stocks in relation to their April values. In most years, the stocks are reduced by 6 to 10 million tons while there are three years with higher and two years with lower releases. For most years with high stock releases between April and October, the January stocks were particularly high compared to the April stocks whereas for the years with low stock releases the January stocks often were low compared to the April stocks. This provides a rationale to use both the April and the January stock levels for regressing the October stock levels because the January stock levels then provide additional information about the time trend which is not included in the April stock levels. The April stocks are then expected to have a positive and January stocks to have a negative influence with the absolute coefficient of the latter being smaller than the one of the former. Hence, the regression equation for the October stocks O_t reads as

$$O_t = \gamma_1 + \gamma_2 J_t + \gamma_3 A_t + e_t \tag{5.1}$$

with γ_1 being the constant, J_t being the stocks in January and A_t being the stocks in April.

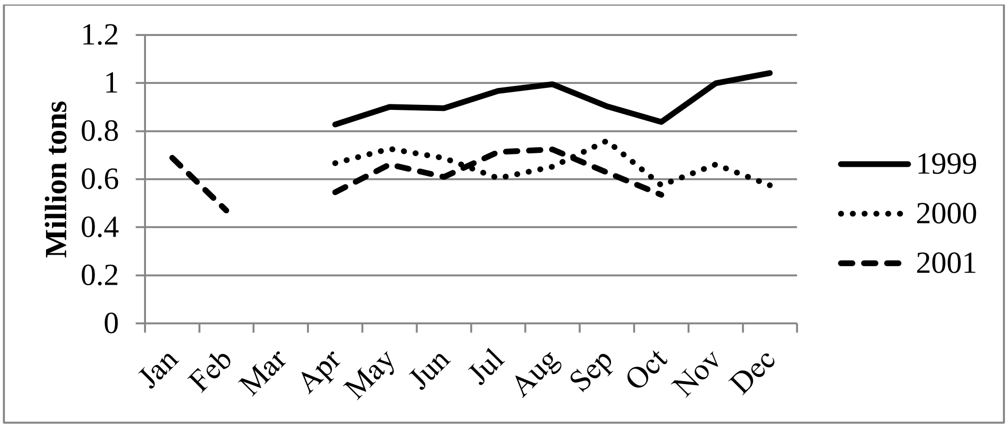

Figure 5.4: Monthly rice offtakes from the public stocks

Note: Own illustration with raw data from FCI.

Three regressions are performed with different dependent variables (Table 5.1), once including both J_t and A_t as well as one specification including only J_t and one with A_t only. As earlier years are more important for the estimation and for testing if the coefficients change over time, specification (4) was added which uses weighted least squares and gives twice the weight to the observations before the year 2000 compared to those afterward. However, this construction is somewhat arbitrary. Specification (5) shows the results for a first difference estimation. All results fully meet the expectations and the high R^2s indicate a very good fit of the model. April stock levels are highly significant and positive in all specifications. The size of the coefficient changes depending on whether January stocks are included. January stocks are always significant and negative unless April stocks are excluded. This is a result of the dynamic discussed above, implying that higher January stocks reduce the October stocks, possibly because of high stock outs if stock levels are ample over a longer time period. If April stocks are not included, higher January stocks just lead to higher October stocks with a coefficient which is statistically not different from the April stocks in specification (2) where no other variables are included. Then, the effect that high stocks over a long time period reduce the ending stocks in October cannot be observed any more. The weighted least squares estimation shows that the coefficients are not statistically different if the years before 2000 receive twice the weight of the observations from 2000 onward.

Overall, the October stocks can be estimated very well this way as indicated by the high R^2 in all specifications. Specification (1) is used to forecast the October stocks for the years before 1990 where only January and April stock levels are available. This specification has the highest R^2, a high F statistic and low BIC. Furthermore, it makes use of the additional information provided by the January stocks which allows for a short-term time trend.

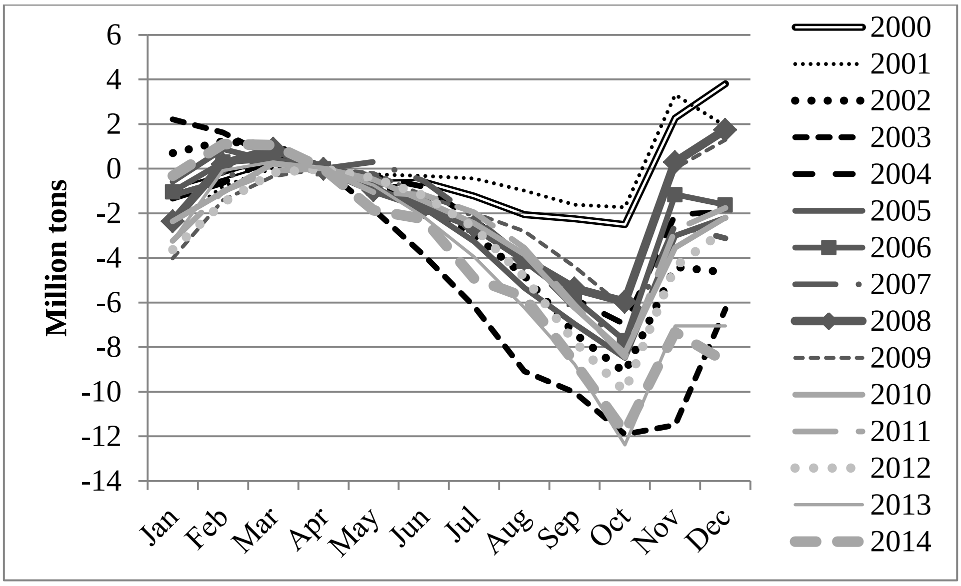

Figure 5.5: Change of public rice stocks relative to each year's April stocks

Note: Own illustration with raw data from FCI

Table 5.1: Regression results for the public October rice stocks

	(1)	(2)	(3)	(4)	(5)
Estimation	OLS	OLS	OLS	Weighted LS	FD
January Stocks	$-.689^{*}$		$.749^{***}$	$-.569^{*}$	$-.84^{*}$
	(.391)		(.081)	(.292)	(.344)
April Stocks	1.39^{***}	$.759^{***}$		1.25^{***}	1.63^{***}
	(.375)	(.057)		(.275)	(.338)
Constant	-.02	$-.023^{*}$	-.011	-.012	-1.9e-03
	(.012)	(.013)	(.015)	(.014)	(5.2e-03)
Adj R^2	.835	.808	.686	.833	.784
R^2	.849	.816	.699	.845	.803
F stat	95	175	85.5	60.8	29.7
BIC	-103	-102	-89.3	-107	-106
Observations	25	25	25	25	24

Notes: Own illustration. Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

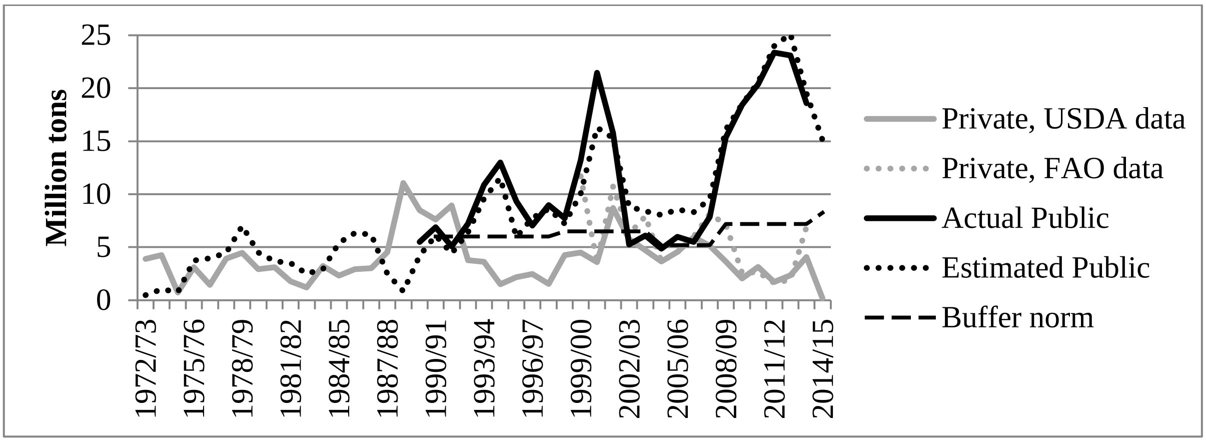

Figure 5.6: Private (grey) and public (black) closing rice stocks

Notes: Own illustration. Raw data obtained from different sources: public stock data from FCI; total stock data from which private stocks are calculated from USDA and FAO (via AMIS). See text for a description how closing public stocks before 1990 and for 2015 are predicted. While public and private stocks are negatively correlated with a coefficient of -0.36, private stocks can better be described when other control variables are accounted for.

Besides looking at the R^2, it is also possible to compare the estimated public stock levels with the actual ones (Figure 5.6). The estimated stock levels clearly follow the observed ones, however, for extremely high or low values the estimation does not perform as well. For the subsequent analysis, the predicted public stock levels are only used for those years, where actual data is missing. Figure 5.6 also shows the private stock levels which are calculated by subtracting the public from the USDA or FAO provided total stock levels. Stock levels from both sources show a similar dynamic but differ substantially in individual years. While the USDA data is available even before 1972/74, the FAO data only starts in 1999/2000. The October buffer norm experienced only minor changes over the years.

5.5 Method to estimate public storage

In contrast to private storage, public storage is not driven by price expectations of private market actors but by the way the government intervenes in the market. This section presents a new method for the estimation of public closing stocks and how the regression can be performed with exogenous variables only. The processes affecting the public stocks, i.e. the inflows and outflows during the marketing year, are depicted in Figure 5.1 and the timing in Figure 5.2.

5.5.1 Overview of determinants

As explained in the introduction, the government procures rice at the pre-defined and therefore exogenous MSP without any limits. Even if the MSP follows international prices in the long-run it still remains exogenous for India which is sufficient here. The open-ended procurement can be described as a mixed complementarity problem (described by the ⊥ symbol),

$$P_t - MSP_t \perp 0 \leq M_t \leq \infty \quad , \tag{5.2}$$

where P_t is the market price in year t, MSP is the minimum support price and M_t is the amount procured in this year. This complementarity condition sets the MSP as lower limit for the market price. Some rice is additionally procured through the levy on rice traders. The government gets a fixed state-dependent share (Saini and Kozicka 2014) which can be approximated as

$$L_t = \alpha H_t \quad , \tag{5.3}$$

with L_t being the amount procured, α the average share and H_t the production in year t. The main way to release stocks is through the public distribution system. As explained in the previous paragraph, these stock releases are relatively stable over time. Stock norms are enforced to ensure that stock levels are sufficient to meet the demand of the PDS and other welfare schemes. The Open Market Sales Scheme (OMSS) and public exports are used to release stocks when their levels are significantly above the norm whereas public imports ensure that stocks do not fall below the norms. Decisions about OMSS offtakes, public exports or imports are made ad hoc without clear rules. As public imports hardly ever occurred and were very low (below 100.000 tons) when they occurred, they can safely be ignored. Public exports (PE_t) and OMSS releases ($OMSS_t$) also rarely occurred and were mostly very small when they occurred, but in a few years, public exports were substantial (Figure 5.7). Altogether, the public ending stock levels in year t can then described by the equation

$$X_t^{public} = (1 - \delta) X_{t-1}^{public} + M_t + L_t - PE_t - OMSS_t - PDS_t + e_t \quad , \tag{5.4}$$

where δ describes the stock losses due to deterioration (the implicit assumption is that these are constant over time and not dependent on the stock levels), PDS_t the offtakes for the PDS and other welfare schemes, and e_t is the error term which may capture leakages or other not-considered factors. The procurement is separated into two parts, M_t which describes the procurement via the MSP and L_t which describes the procurement via the levy.

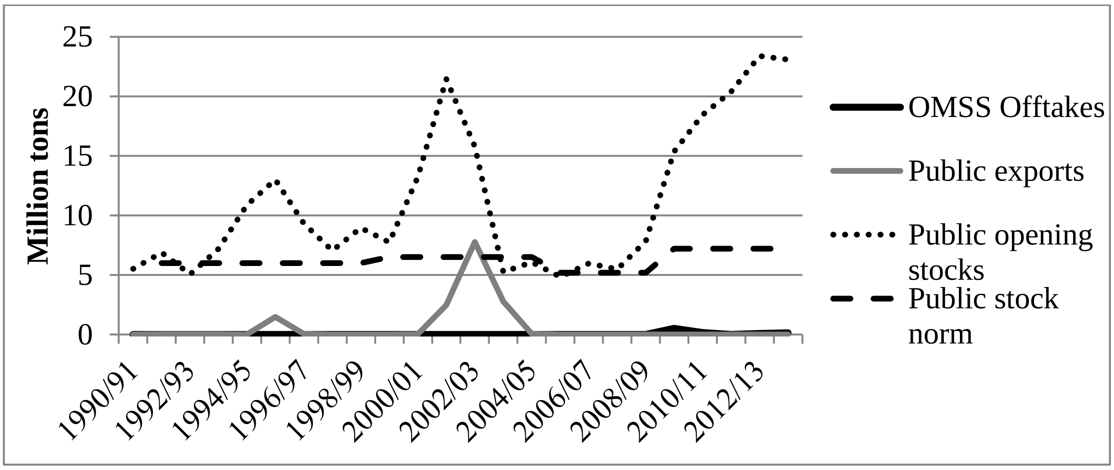

Figure 5.7: Public exports, OMSS offtakes, opening stocks, and stock norm

Notes: Own illustration with raw data from FCI.

5.5.2 Impact of the minimum support price

Procurement depends on the market prices but can be expressed in terms of the other variables. To illustrate that, it is assumed that there is a producer region where the local supply-demand equilibrium price is below the binding MSP while in the so called consumer region (e.g. urban areas) production is costly and therefore the local supply-demand equilibrium is above the MSP (Figure 5.8). Without trade, the local equilibrium would determine the price. With trade, the price in the consumer region is determined by the demand curve and the quantity imported from the producer region which itself depends on the MSP. In the given example, the producer region consumes a share of the local production, another share of it is exported and the last share is procured by the government at the MSP. The trade costs determine the price difference between the regions.

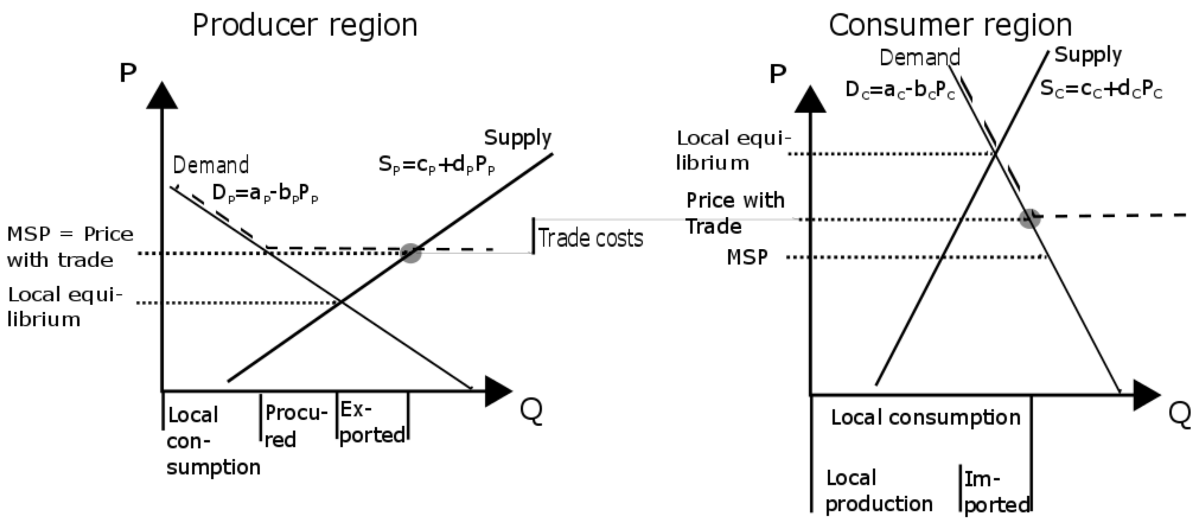

Figure 5.8: Illustration of how policy variables and trade affect public stocks

Notes: Own illustration. The MSP and trade between the producer and consumer region influences the regional prices and quantities ex- or imported, consumed, or procured by the government.

If the government would raise the MSP by ΔMSP, the share of the quantity consumed within both the producer region as well as the consumer region would linearly decline with the MSP increase. The linear decrease of the former equals $\Delta D_P = \Delta MSP \cdot \mathrm{b_P}$ while the latter decreases by $\Delta D_C = \Delta MSP \cdot \mathrm{b_C}$. In addition, while there would be a linear increase of production in the producer region ($\Delta S_P = \Delta MSP \cdot \mathrm{d_P}$) and in the consumer region ($\Delta S_C = \Delta MSP \cdot \mathrm{d_C}$), the trade flow would also decrease linearly with the higher MSP by $\Delta MSP \cdot (b_C + d_C)$. In contrast, the quantity procured would increase with the rising MSP by

$$\Delta M_P = \Delta MSP \cdot (d_C + b_C + d_P + b_P)\,. \tag{5.5}$$

This equation also describes the effect of lowering the MSP. It is important to note that the procurement changes linearly with the change in the MSP as long as the MSP is above the local equilibrium in the producer region and the MSP plus the trade costs are below the local equilibrium in the consumer region. If the first condition is not fulfilled, a MSP decrease would not change the quantity procured. The change in the procurement if the latter condition is not fulfilled is not a priori clear and will be examined in the subsequent sections. For the example illustrated in Figure 5.8, the grey dots indicate the equilibrium state of the system.

Under the assumption that there are more than two regions, the behavior depends on the demand and supply curves in all the regions. To illustrate the line of argumentation, it is first assumed that there are three regions only, one producer region, one consumer region, and one which switches when the MSP increases above a certain threshold (Figure 5.9, parameters of the switching region are indicated by the index S). Before the MSP is increased, the procurement at the "old MSP" can be calculated as:

$$\begin{aligned} M_{all} &= S_P - D_P + D_S - H_S + D_C - H_C \\ &= c_P - c_S - c_C - a_P + a_S + a_C + P_P(d_P + b_P) - P_S(d_S + b_S) - P_C(d_c + b_c)\,, \end{aligned} \tag{5.6}$$

where the prices in the producer region equals the MSP ($P_P = MSP$) and the prices in the other region equal the trade costs T plus the MSP ($P_S = P_C = MSP + T$). Here, it is assumed that the trade costs between all regions are the same, i.e. $T = T_{P\leftrightarrow S} = T_{P\leftrightarrow C} = T_{S\leftrightarrow C}$. Similarly as before in equation (5.5), a very small increase in the MSP, i.e. one which would still leave the switching region as an importing region, would increase the procurement by

$$\Delta M_P = \Delta MSP \cdot (d_C + b_C + d_P + b_P + d_S + b_S) \tag{5.7}$$

because all prices would simply be increased by ΔMSP. Hence, there is only an additional term added to equation (5.5) which represents the need for exports from the producer region, i.e. the region where all the procurement takes place, to the switching region. This implies $\Delta MSP \leq P_S^* - MSP - T$ and is represented by regime 1 in Figure 5.10.

If the MSP is increased to such an extent that the switching region becomes a self-sufficient region which does not import any more but also does not yet procure anything, i.e. $P_S^* - MSP - T < \Delta MSP \leq P_S^* - MSP$ (regime 2 in Figure 5.10), then the change in procurement in the producer region changes to:

$$\Delta M_P = \Delta MSP(d_C + b_C + d_P + b_P) + \underline{\Delta MSP}(d_S + b_S). \tag{5.8}$$

Here, $\underline{\Delta MSP}$ is that part of the MSP increase, which raises the MSP up to the equilibrium price (P_S^*) in that region minus the trade costs T, i.e. $\underline{\Delta MSP} = \min(\Delta MSP, P_S^* - MSP - T)$. The minimum function ensures that $\underline{\Delta MSP}$ is equal to the change in the MSP if $\Delta MSP \leq P_S^* - MSP - T$ whereas it is equal to $P_S^* - MSP - T$ if $\Delta MSP \geq P_S^* - MSP - T$, i.e. if the MSP is raised up to the point such that no more imports into the switching region occur. This definition ensures that equation (5.7) is included as a special case in equation (5.8). As long as the new MSP is not greater than the equilibrium price in the switching region, i.e. $MSP + \Delta MSP \leq P_S^*$, equation (5.8) describes the full procurement because no procurement takes place in the switching region. Thus, the marginal procurement will be reduced, once the change in the MSP, ΔMSP, is larger than $P_S^* - T - MSP$ (but still smaller than $P_S^* - MSP$) because no more exports take place from the producer to the switching region.

If the change of the MSP, ΔMSP, is larger than $P_S^* - MSP$, such that the new MSP, $MSP + \Delta MSP$, is larger than the equilibrium price in the switching region, procurement will also start to take place in this region. As long as $\Delta MSP \leq P_S^* - MSP + 2T$ holds, no exports occur from the switching region (regime 3 in Figure 5.10). Then, the additional procurement for both the producer and the switching region sums up to:

$$\Delta M_P + \Delta M_S = \Delta MSP(d_C + b_C + d_P + b_P) + \underline{\Delta MSP}(d_S + b_S) + \overline{\Delta MSP}(d_S + b_S)\,. \qquad (5.9)$$

Here, $\overline{\Delta MSP}$ represents that part of the change in MSP which is above the equilibrium price P_S^*, i.e. $\overline{\Delta MSP} = \Delta MSP - T - \underline{\Delta MSP}$.

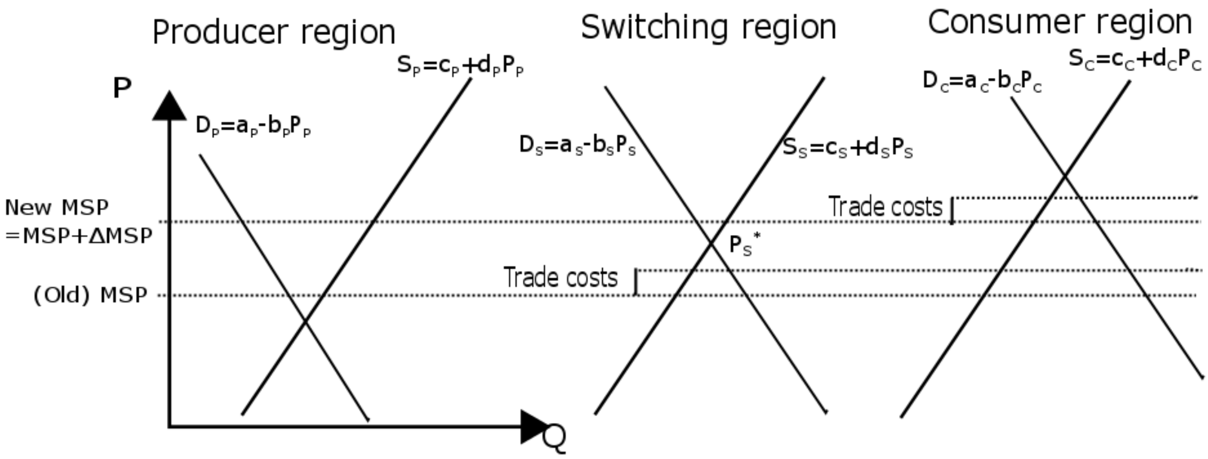

Figure 5.9: Illustration of the impact of MSP changes for switching markets

Note: Own illustration.

If the MSP is raised even higher, i.e. $\Delta MSP > P_S^* - MSP + 2T$ (regime 4 in Figure 5.10), not only procurement occurs in the switching region but also exports from the switching to the consumer region take place. However, using equation (5.6) and considering that all prices are then increased by $\Delta MSP = \underline{\Delta MSP} + 2T + \overline{\Delta MSP}$ shows that the functional relationship does not change and equation (5.9) can still fully explain the change in procurement due to a change in the MSP within this region.

If changes within each regime are regarded independently, i.e. price changes with the previous price and the price afterward being in the same regime are considered, then it turns out that the change in procurement for regime one, three, and four can be described as

$$\Delta M_P + \Delta M_S = \Delta MSP(d_C + b_C + d_P + b_P + d_s + b_S)\,, \qquad (5.10)$$

whereas in regime two the change in procurement is

$$\Delta M_P + \Delta M_S = \Delta MSP \cdot (d_C + b_C + d_P + b_P)\,. \tag{5.11}$$

Thus, due to the stop of exports into the switching region for prices within regime two combined with the missing procurement in this region for prices below the equilibrium price, the marginal change in procurement is reduced in this region. For all other regimes, the marginal procurement for all regions combined remains the same because either procurement in the producer region is changed due to changing exports to the switching region or procurement directly takes place in the switching region.

If trade costs are negligible, then equation (5.10) describes the change of procurement based on the change in the MSP for all regimes. If, however, procurement would not take place in the switching region, then the regime three would be the same as regime two for a switching market because trade costs would apply for exports to regions with procurement.

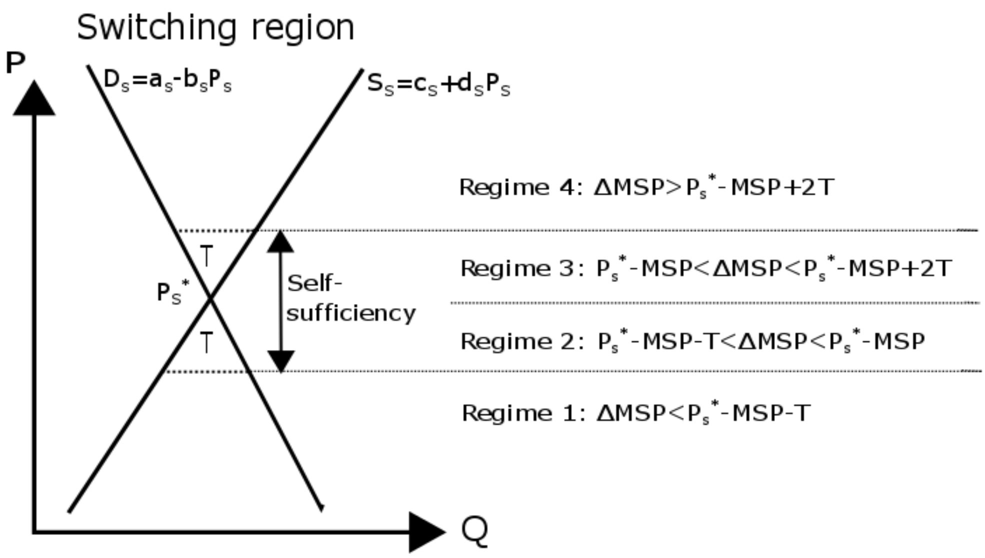

Figure 5.10: Four different regimes for price changes in the switching region

Note: Own illustration.

The previous explanations illustrated how a price change will affect the total procurement if a region changes its status regarding its degree of self-sufficiency. The extension to more than three regions is now straightforward: All regions can be classified into strict producer, strict consumer, and switching regions depending on the level of variability in the MSP which is considered. Then, the above principles are applied to the three groups. Instead of having two kinks in the marginal procurement, the number of kinks can be up to twice the number of switching regions. The location of the kinks as well as the coefficients of how changes of the MSP affect procurement depends on the precise structure of all markets, i.e. on all parameters of the supply and demand curves. However, these cannot be measured. Nevertheless, various assumptions justify applying an approach where a change in the MSP linearly affects the change in procurement, thus formally

$$\Delta M_{all\ regions} = \Delta MSP \cdot const\ , \tag{5.12}$$

where the constant depends on the precise structure of the markets ($a_i, b_i, c_i, d_i\ \forall i$). These assumptions, of which only a single one needs to be fulfilled, include the following:

- Trade costs are negligible, for example, because the market are very close to one another
- The number of switching markets is very low compared to the number of producer and consumer markets
- The distribution of switching markets is sufficiently dense and their density sufficiently constant over the considered price range

If only a single one of these assumptions holds, equation (5.12) can describe the change in procurement which is caused by a change of the MSP. Thus, this linear relationship builds the basis for the further analysis.

5.5.3 Production impact

Apart from the MSP, production shocks influence the procurement. On the one hand a negative production shock reduces the levy which is captured by α in equation (5.3). On the other hand it reduces the procurement via the MSP. This is illustrated by the dashed lines in Figure 5.8. The production curve in Figure 5.8 is interpreted as the planned private supply (opening stocks + production) so a shock would lead to a horizontal shift from this curve. A production shock, be it negative or positive, leads to a movement of the equilibrium along the dashed lines. While a small supply shortfall in the producer region reduces procurement, it does not affect trade or the consumer region. In contrast, a large shortfall would reduce procurement to zero and then raise prices in both regions. A small shortfall in the producer region would affect the quantities traded but not the prices, whereas a big production abnormality could either lead to reduced consumption (if procurement is reduced to zero in the producer region) or lead to exports from the consumer regions for an unusually high supply level (dashed line toward the right).

5.5.4 Demand impact

Demand changes may influence procurement through a change in market prices. In India, the demand fluctuated with production in the past (Figure 5.11; the correlation coefficient is 0.94); however, this fluctuation was not fully represented in the real prices as in only a few years production shortfalls led to high prices, whereas prices still remained relatively low in other years with production shortages. As a result, in many years the production levels provide more information about the demand than prices do. Hence, the influence of demand on stocks through market prices is captured in the production term. As a result, no prices are explicitly included. However, international as well as Indian wholesale prices have been tested for both private and public stocks but, as expected, turned out to be insignificant.

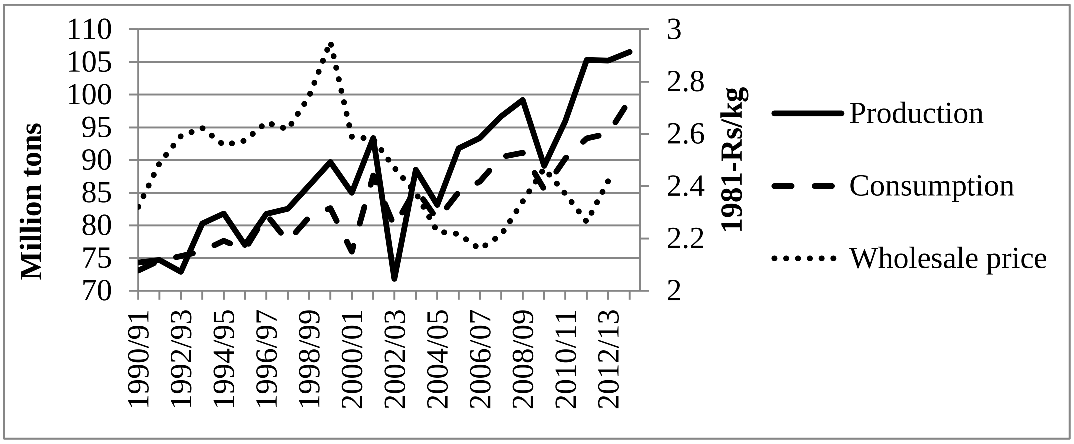

Figure 5.11: Production, consumption and WPI-deflated wholesale prices

Notes: Own illustration. The base year is 1981. Production and consumption (left axis) data is obtained from the USDA, prices (right axis) from MOSPI.

5.5.5 Impact of export bans

Export bans may also influence public stocks as there are fewer or no opportunities for selling rice on international markets and therefore government agencies might be one of the few choices left for farmers and traders to sell their grains. In Figure 5.8 it can be seen that if exports from the producer regions are banned, the quantity which was supposed to be exported will be procured instead. Under the assumption that Indian exports cannot influence world prices significantly and transportation costs are relatively stable, the additional quantity procured can be approximated by a constant.

Combining these effects of the MSP, supply levels, and export bans on procurement, yields

$$M_t + L_t = \kappa\, MSP_t + \lambda\, S_t + \xi\, \mathrm{B_t} \tag{5.13}$$

where S_t is the private market supply, i.e. production plus opening stocks, and $\mathrm{B_t}$ is a dummy variable for export bans. As the export ban dummy is stationary, it does not need to be detrended as the other variables describing rice quantities or prices will.

5.5.6 Impact of public exports and OMSS releases

Public exports and OMSS releases depend on the stock levels but occur in very few years only and are mostly low. In general, they are used to enforce that stocks fulfill the buffer norms. To approximate the public exports and OMSS releases, it is therefore assumed that these represent a certain share of the stock level above the norm $\left(X_t^{public} - N_t\right)$. This behavior results in the following equations:

$$PE_t = \beta \max\left(0, X_t^{public} - N_t\right) = \beta\left(X_t^{public} - N_t\right)\theta\left(X_t^{public} - N_t\right) \tag{5.14}$$

$$OMSS_t = \mu \max\left(0, X_t^{public} - N_t\right) = \mu\left(X_t^{public} - N_t\right)\theta\left(X_t^{public} - N_t\right) \tag{5.15}$$

Here, $\theta(\cdot)$ is the Heaviside step function. Decisions on such releases as well as the processing of these releases take a lot of time and are made cautiously and delayed (Figure 5.7). Therefore, it is more appropriate to replace the current stock levels by last year's stock levels for the release trigger[19], represented by the Heaviside step function in the corresponding equations (5.14) and (5.15). Then, the corresponding part of the stock equation can be expressed as

$$X_t^{public} = (\mu + \beta)\left(X_t^{public} - N_t\right) \theta\left(X_{t-1}^{public} - N_t\right) + (1 - \delta)X_{t-1}^{public} + \cdots \tag{5.16}$$

For the years with $X_{t-1}^{public} < N_t$ this reduces to

$$X_t^{public} = (1 - \delta)X_{t-1}^{public} + \cdots \tag{5.17}$$

and for the other years to

$$X_t^{public} = [(\mu + \beta) + (1 - \delta)]X_{t-1}^{public} + (\mu + \beta)N_t + \cdots \tag{5.18}$$

Equation (5.16) could be used for the estimation if the stock norms were known for all years. But as stock norms are only known from 1989 onward, the sample could be split up into two subsamples with $X_{t-1}^{public} < N_t$ and with $X_{t-1}^{public} > N_t$ and then estimated with equations (5.17) and (5.18) separately. However, as the number of observations is low, a further reduction should be prevented. Hence, the full sample is estimated based on equation (5.18) which may lead to a small bias in the parameter $(1 - \delta)$ as the missing term is slightly correlated to X_{t-1}^{public} via Heaviside's step function but the other parameters remain unaffected. As releases are rare and usually small, the bias is expected to be very low. In addition, the estimation is also performed based on equation (5.16) for the years from 1989 onward where the norms are known. Yet, OMSS stock releases and public exports are done cautiously and, with one exception, substantial releases (>65.000 tons) occurred only when the opening stocks were higher than twice the stock norms (Figure 5.7). Hence, the threshold for these releases is set to twice the stock norms.

5.5.7 Public storage regression equation with all determinants

Under the assumption of relatively staple consumption-detrended PDS offtakes, three policy variables can be captured in the estimation: the stock norms, the MSP, and the export bans. Using equation (5.13) and (5.16) and the assumptions above, equation (5.3) can be transformed into

$$X_t^{public} = \alpha_0 + \alpha_1 X_{t-1}^{public} + \alpha_2 MSP_t + \alpha_3 S_t + \alpha_4 \mathrm{B_t} + \alpha_5\left(2\,X_{t-1}^{public} - N_t\right)\theta\left(2\,X_{t-1}^{public} - N_t\right) + e_t \tag{5.19}$$

As a result, the public stocks are expressed in terms of exclusively exogenous variables. Prices or other exogenous variables are not included, albeit international as well as Indian wholesale prices were tested for both private and public stocks but, as expected, turned out to

[19] Of course, only the stock levels for the trigger are lagged, not the stocks from which the exports/releases are actually taken.

be insignificant. To ensure stationarity of the time series, non-price data was detrended by the consumption trend as explained in the previous section and price data was deflated by the consumer price index. The general equation describing the public stocks is then given by:

$$\frac{X_t^{public}}{D_t^{trend}} = \alpha_0 + \alpha_1 \frac{X_{t-1}^{public}}{D_t^{trend}} + \alpha_2 MSP_t + \alpha_3 \frac{S_t}{D_t^{trend}} + \alpha_4 B_t + \alpha_5 \frac{2\,X_{t-1}^{public} - N_t}{D_t^{trend}} \theta\left(2\,X_{t-1}^{public} - N_t\right) + e_t \quad (5.20)$$

where X_t^{public} is the public closing stocks in the marketing year t, D_t^{trend} is the consumption trend, MSP_t is the minimum support price, S_t is the private market supply (i.e. production in the beginning of the marketing year plus beginning private stocks), B_t is an export ban dummy, and N_t is the buffer norm for the public ending stocks. The error term e_t captures leakages and other factors which are not considered.

As a robustness check, the same regressions are performed on the levels (specification 1 and 2 in Table 5.2) and on the first differences (specification 3 and 4); in both cases, one model including the buffer norm and one without norm is presented as the norm reduces the number of observations and, in particular the degrees of freedom. If the norm is included, the regression uses only the non-extended USDA series of stocks with the exception of the year 2015 where the ending stocks are still predicted.

5.6 Method to estimate private storage

Estimating private storage requires knowledge about the behavior of private stockholders. Theoretically, private stocks should be driven by price expectations of stockholders. Prices and price expectations themselves are a result of supply and demand expectations of different market agents, including traders, farmers, and consumers. However, unlike current prices, private agents' price expectations or expectations about supply and demand in the future are hard to observe. Even if asked, agents may face incentives to misreport if they could benefit from private knowledge or are not willing to invest time into reporting. Moreover, risk-averse agents such as small-scale farmers may directly use storage for supply and consumption stabilization rather than profit maximization. Therefore, price expectations are included only indirectly, by using the approach presented in chapter 4. There, a piece-wise linear reduced-form storage equation is derived which is based on the competitive storage model with traders and price responsive producers in a two country setting. Instead of using price expectations, which are a result of supply and demand expectations, supply and demand fundamentals are directly used to find a piece-wise linear approximation of private carry-over stocks. Hence, price expectations are used to describe private stocks but they are not explicitly modelled. This study uses that approach with three simplifications. First, it is limited to the case of one country where the rest of the world (RoW) is only included by the expected surplus within RoW. Second, demand shocks are excluded because demand in India mostly follows production (Figure 5.11) and because the number of observations is low and, hence, requires limiting the number of explanatory variables which are used. Furthermore, GDP shocks, which are used as an approximation of demand, were tested but turned out to be insignificant and were therefore excluded. Third, the storage rule is assumed to be fully linear without a kink which originally occurs when stocks are zero. Assuming full linearity without a kink is justified by the private ending stocks always being clearly above zero, even when estimated operational stocks are subtracted. Explanations of stocks being always strictly positive range from convenience yield approaches postulating an intrinsic possession value (Brennen 1958; Working 1949), mismeasurement and aggregation issues (Benirschka and Binkley 1995; Brennan et al. 1997), and diverse motives of stockholders (Carter and Giha 2007). However, a Tobit model was tested to account for nonlinear storage behavior. This allowed the use of a piece-wise linear function by introducing a cutoff point, i.e. a minimum level of stocks which represents the operational stocks. Yet, the results of this Tobit model were not statistically different from the regular IV regression. In addition, due to the limited number of observations there should be a minimal amount of additional parameters and restrictions on the degrees of freedom imposed on the model. In conclusion, these reasons provide the rationale to test different specifications for robustness but to remain with the simplest applicable version possible.

Overall, three important variables need to be included based on the discussion above: First, public closing stocks to control for crowding out of private closing stocks; second, supply at the beginning of the marketing year to account for future price expectations as well as the influence on public stocks through the levy; and third, an export ban dummy or the surplus of the rest of the world as alternative measures to control for export opportunities and related expectations of stockholders. Public storage can be important because procurement takes grains from the market and large stocks may also increase the government’s PDS distribution quantities, OMSS offtakes, and exports from public stocks. Therefore, public stocks may affect price expectations of private stockholders. While the market supply is fixed to a large extent (opening stocks + kharif production) at the beginning of the marketing year and fully fixed at the time of the rabi harvest (Figure 5.2), procurement takes place during the whole marketing year. Restrictions on private market actors activities such as restrictions on stock levels through the Essential Commodity Act cannot be considered as they are often badly documented, not enforced, and imposed on the state level and hence hard to aggregate on the national level (see section 5.2). The general equation describing the private stocks is then given by:

$$\frac{X_t^{priv}}{D_t^{trend}} = \alpha_0 + \alpha_1 \frac{S_t}{D_t^{trend}} + \alpha_2 \frac{X_t^{public}}{D_t^{trend}} + \alpha_3 B_t + \alpha_4 \frac{L_t}{D_t^{trend}} + e_t \tag{5.21}$$

where X_t^{priv} and X_t^{public} are the private and public closing stocks in the marketing year t, D_t^{trend} is the consumption trend, S_t is the total market supply, L_t is the expected surplus in RoW calculated as the actual production minus the expected demand (from the demand trend), and B_t is an export ban dummy. This stationary export ban dummy is expected to have a linear influence as discussed in section 5.5.5. As closing public sector stocks are considered for the same marketing year as the estimated private closing stocks, endogeneity problems may arise. Hence, the regressions are estimated using the instrumental variables technique.

The public closing stocks are instrumented by the exogenous MSP and the public closing stocks of the previous year which are the public opening stocks of the current year. These two variables are found to be the main driver in the section on public stocks and the other important variables are included as non-excluded instruments in the regression. The public opening stocks are used as an instrument because public stocks only change slowly and are not a perfect substitute of private market supply as they follow different dynamics. In particular, public stock releases react much less flexible than private stock outs. The MSP is used as the second instrument because it is the main driver of the change in public stocks (see sections 5.5 and 5.7) and it is exogenous because it is fixed before the planting season starts (Figure 5.2). It influences production and public stocks but there is no other channel through which it influences private stocks. The MSP shapes the demand of the government through the open-end procurement which is captured by including (MSP-instrumented) public stocks but apart from that it does not influence market prices or price expectations. In addition, the current MSP does not matter for future demand or price expectations because private stocks occur at the end of the marketing year, i.e. long after the harvest is brought in and the new MSP for the next marketing year is announced (Figure 5.2). The production is fixed to a large extent already when the bigger kharif season is ending. After the harvest of the rabi season has started, there should be only minor changes to the expected production for a specific marketing year. However, the ending stocks only occur a few months later and hence the production is exogenous to these. As production is controlled for separately, the production effect of the MSP can be neglected and the procurement price only influences expected prices via the procurement which is the desired effect. In addition, because the market supply is used in the regression, i.e. opening stocks plus production, the effect of the MSP on this variable is negligible which also manifests itself in a low correlation coefficient of only 0.21. Overall, these reasons lead to the belief that the MSP is a good instrument for the public stocks but otherwise does not influence the private stocks.

Different test statistics are calculated to ensure the validity of the instruments. As robust standard errors are applied, the Kleibergen-Paap rk LM statistic is used to test for underidentification of instruments (Kleibergen and Paap 2006). Weak identification is tested with the Kleibergen-Paap rk Wald F statistic, overidentification with the Hansen J statistic (Hansen 1982). Contrarily to what is often believed, the latter does not test the validity of instruments but rather their coherency, i.e. whether all instruments identify the same vector of parameters (Hausman 1983; Parente and Santos Silva 2012).

A number of different additional tests are performed. Regressions are performed as IV regressions on the levels (specification 1-3 in Table 5.3), OLS regressions on the levels (specification 4), IV regression on the first differences (specification 5), and OLS regression on the first differences (specification 6). For the IV regressions, the 2SLS, two-step GMM, limited information maximum likelihood (LIML; Anderson and Rubin 1950; Anderson 2005), and CUE GMM estimators (Hansen et al. 1996) were used and compared. Robust standard errors were applied in all cases. The estimated coefficients for all estimators were statistically not different from one another. Therefore, only the results for the CUE GMM estimator are presented as this estimator, just as the LIML estimator (Flores-Lagunes 2007), is reported to have better finite sample properties than the 2SLS (Hansen et al. 1996). At the same time, in contrast to the LIML estimator, the CUE GMM estimator is also applicable if heteroscedasticity is present (ibid.). The regressions are performed with the user written command ivreg2 (Baum et al. 2007) in Stata 13. As a further robustness check, the included endogenous variables are changed (specifications 1-3) and the same regressions are repeated on the non-extended USDA data from 1990 onward and on the FAO data (appendix; Table 8.3).

5.7 Results for public rice stocks

Both level and first differences regression results for public stocks are in line with prevailing expectations discussed in the previous sections (Table 5.2). As expected, the MSP turns out to be an important driver of public stocks. It has a very high coefficient which is highly significant in all specifications. As the MSP is deflated (and, as a result, is stationary) the coefficient cannot directly be interpreted by using the MSP in Indian Rupee. Instead the deflated MSP needs to be multiplied by the consumption trend and the respective coefficient, to obtain the total contribution of the MSP to stocks in a specific year. Examples are provided in the discussion of Figure 5.12.

The private supply is another important factor which always has a positive coefficient and highly significant impact. The coefficient of 0.299 in the first specification implies that 1 million tons of additional production leads to a 0.3 million ton increase in ending stocks. The lagged public closing stocks (which are the public opening stocks) are significant in all specifications. Their coefficient of 0.767 in the first specification means that every ton of opening stocks leads to 0.767 tons of closing stocks. This is a result of the slow changes which public stocks experience, i.e. a large fraction of the closing stocks is already determined by the opening stocks. The stocks above the buffer norm are insignificant in both specifications and hence no conclusion about how the buffer norms influence public stocks can be drawn. The overall low level of public exports, OMSS releases and in particular public imports (Figure 5.7) however support the finding that there is no major impact on public stocks. Finally, the export ban is, as expected, positive and significant in all specifications implying that export bans lead to higher public stocks. The very high R^2 indicate a good model fit. The similarity of the results between the first differences and the level specification support the robustness of the model.

Table 5.2: Regression results for the public closing stocks

	(1)	(2)	(3)	(4)
Estimation	Levels	Levels	FD	FD
Public Opening	.767***	1.09**	.423*	.901**
Stocks	(.113)	(.402)	(.209)	(.385)
MSP	.82***	1.05**	1.28***	1.26***
	(.299)	(.476)	(.26)	(.386)
Private Supply	.299***	.421***	.186**	.341**
	(.05)	(.147)	(.074)	(.137)
Export Ban	.033**	.035**	.041**	.042**
	(.013)	(.014)	(.019)	(.018)
Above Buffer		.811		.773
Norm		(.648)		(.558)
Constant	-.522***	-.735***	3.8e-04	6.2e-04
	(.084)	(.196)	(5.3e-03)	(7.9e-03)
BIC	-150	-90.4	-138	-75.1
R^2	.772	.823	.458	.531
Observations	40	25	39	24

Notes: Own illustration. Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The private supply does include the production and the private opening stocks, but not the public opening stocks are they are included separately.

Figure 5.12 illustrates the predicted and actual changes of public stocks as well as the driving factors of these changes according to specification 1 for the years from 2002 to 2015. This sheds some light on the determinants of some observed stock changes in the past. The biggest ever stock decline in India from October 2002 to October 2003 is mostly attributable to the low level of supplies, the reduction of public stocks in the previous year and the reduction of the MSP in real terms – even though it was constant in nominal terms. When the world food crises started in 2007, the government of India introduced an export ban which led to public stocks rising by 2.9 million tons in addition to a 1 million ton increase due to high supply levels. In total, this yielded a substantial increase in stocks despite exceptionally high prices on the world market. In the subsequent year, public stocks soared. The MSP was raised from 6450 INR in 2007/08 to 9000 INR in 2008/09 which is a 40% increase in nominal terms and a 29% increase in real values. According to specification 1 of the results, this change in the support price resulted in 4.9 million tons higher public stock levels in October 2009 (Figure 5.12). Other factors such as supply levels and the lagged public stocks had a comparably small contribution to the stock increase. In general, the production also responds to the MSP (Kozicka et al. 2015b) and this can be observed in 2008/09 where a record harvest of almost 100 million tons was achieved. This increased public stocks by another 0.5 million tons. It seems that the Indian government was not fully aware of the expected increase in public stocks due to such a massive increase of the MSP. Clearly, this exceptional raise of the support price would have required comprehensive OMSS offtakes. However, these offtakes did not take place and thus public stocks skyrocketed. Had there not been a large negative production shock in the marketing year 2009/10, stocks would have soared even further. Despite this major shortfall, stocks still increased. In recent years, stock levels were brought down by allowing exports, by a low production in 2014/15 and by low procurement prices (except in 2012/13). However, stock levels mostly fell relatively to the consumption levels as can be seen by the contribution of the constant. In absolute levels, their decrease is still relatively limited.

This study does not attempt to calculate an optimal rule for public stocks as that would require defining objective functions and welfare functions and is therefore far beyond the scope of this study. It would also involve judgments about how to distribute welfare between consumers and producers. However, any reasonable objective function would require large stock releases in times of production shortfalls and high prices. As these did not happen and stock levels even increased during the world food crisis in 2007/08, it is clear that from the ex-post perspective, the stockholding policies from the Indian government were far from optimal. Indeed, as discussed above, it seems that the problematic interactions of conflicting policies which resulted in stock increases were not anticipated by policy makers.

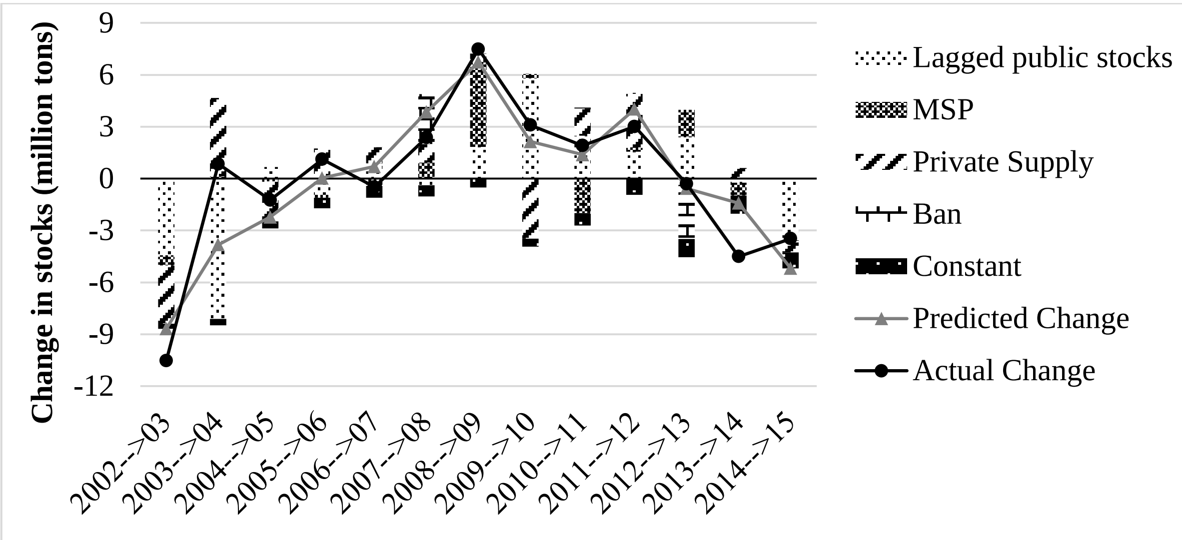

Figure 5.12: Actual and predicted changes of public closing stocks

Notes: Own illustration. The changes (lines) and the driving factors behind these (bars) according to model specification (1) in Table 5.2. As the closing stocks are the stocks at the beginning of October, the “2002-->03” stock change refers to the change from October 2002 to October 2003.

5.8 Results for private rice stocks

Private stocks are estimated following equation (5.21) with IV and direct OLS techniques for the levels as well as first differences (Table 5.3). The supply now contains the private supply and the public opening stocks because these are not included separately as in the public stock regression. Overall, the different specifications provide fully consistent results, i.e.

coefficients have a similar magnitude and are statistically significant in all cases. Total (market) supply is found to be one of the main drivers of private storage, which is in line with the theory of competitive storage (Gustafson 1958; Williams and Wright 1991) and the expectation from the theoretical approach (chapter 4). More grain is stored in years of excess supply and this result is consistent in all specifications. If public stocks did not exist, the response of private storage to production could be even greater. Government stocks consistently have a negative and significant impact in all specifications and turn out to be the most important factor. Hence, public storage seems to crowd out private storage substantially; each ton of public stocks reduces private stocks by about half a ton. Again, this finding is in line with the expectations as detailed above and with results obtained by other authors (e.g. Gouel 2013c). However, public storage is no perfect substitute, i.e. it only partly crowds out private storage as its coefficient is statistically smaller than one. A possible explanation is the inertia of decisions on public stock releases. While government interventions are substantial, they are far from following optimal storage rules.

Table 5.3: Regression for the private closing rice stocks

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation	IV-Levels	IV-Levels	IV-Levels	OLS-Levels	IV-FD	OLS-FD
Public Stocks	-.557***	-.648***	-.651***	-.447***	-.494***	-.3***
	(.13)	(.138)	(.152)	(.142)	(.139)	(.097)
Total supply	.323***	.349***	.337***	.261***	.256***	.255***
	(.077)	(.075)	(.08)	(.081)	(.048)	(.049)
Export Ban	.026***					
	(8.5e-03)					
Surplus RoW		.097***				
		(.035)				
Constant	-.295***	-.296***	-.279***	-.21**	-1.7e-03	-2.2e-03
	(.084)	(.076)	(.081)	(.084)	(3.7e-03)	(4.0e-03)
UI: LM / stat	13.3	12.9	11.8		5.38	
UI: LM/ p	1.3e-03	1.5e-03	2.7e-03		.02	
WI: F stat	28	26.9	31.3		25.6	
BIC	-168	-165	-161	-174	-173	-177
R^2	.447	.405	.274	.362	.447	.471
OI: Hansen J/ stat	4.24	2.1	.579		0	
OI: Hansen J/ p	.04	.147	.447			
First-stage R^2	.663	.669	.654		.349	
First-stage F	34.9	37.4	50.2		13.8	
Observations	40	40	40	42	39	41

Notes: Own illustration. Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Statistics used: Underidentification (UI): Kleibergen-Paap rk LM statistic, Weak identification (WI): Kleibergen-Paap rk Wald F, Overidentification (OI): Hansen J. The supply includes the production, private opening stocks, and public opening stocks.

The export ban coefficient is positive and significant as well as the surplus in the rest of the world variable, so banned exports or a worldwide surplus both lead to higher stocks. Speculative private storage in hope of a future harvest failure may become more attractive when current profit margins from trade decrease. The negative constant in the levels estimation indicates evidence for the private storage threshold which is expected from theory. Private stocks seem to respond more strongly to the market supply than public stocks as the coefficients are higher. However, not for all pairs of specifications which one could compare, they are statistically different from one another.

The different test statistics support the validity of the regressions: no evidence is found for underidentification, weak identification, or the non-validity of the instruments with exception of specification (1) where the overidentification test yields a value just below the threshold of 0.05. The high R^2 indicate a very good model fit and the first stage R^2 support the instrument choice. Overall, only closing private stocks are analyzed and no conclusions about intra-annual effects can be drawn due to lack of data on intra-annual private stocks.

5.9 Conclusion

This study develops a novel approach for the estimation of determinants of public stocks for the Indian context. Furthermore, it uses the method developed in chapter 4 and combines it with an instrumental variable approach to quantify determinants of private rice stocks in India. The method for private stocks is based on insights from the competitive storage model and numerical approximation techniques and hence has a solid theoretical foundation. The approach for estimating the public stocks is derived from the specific policy interventions in India and standard supply and demand theory. These methods allow empirically estimating the determinants of private and public stock levels, including the role of actual policies. Instrumental variables are used to address endogeneity issues that are immanent in the analysis of prices, expectations and speculative storage. Levels and first difference specifications are used together with different sub-specifications to deal with methodological issues such as the low number of observations and a remaining uncertainty about the stationarity of some variables. Various test statistics underlined the robustness of the results and the validity of the instruments in the private stock regression where public closing stocks are instrumented by public opening stocks and the minimum support price.

Public stocks are found to be slowly changing and driven by the MSP, private market supply, and export bans. Together, these factors can explain most of the variation in public stocks. Buffer norms are found to be insignificant but that result needs to be interpreted with great caution as very little data on buffer norms could be obtained and buffer norms were rarely altered leading to little variation in the data. Qualitatively, the non-relevance of buffer norms can be explained by the rare use of public imports, exports, or OMSS releases which are designed to prevent deviations from these norms. Hence, norms are set up but rarely enforced. Clearly, from the ex-post perspective, the FCI did not even approximately follow an optimal strategy in their stockholding policies. Calculating optimal rules goes beyond the scope of this study but any reasonable objective function for public stockholders would require stock releases in times of production shortfalls and high prices. As these did not happen in 2007/08 and in other years with supply shortfalls, the FCI seems to be far away from an optimal policy. This claim is further supported by the lack of well-defined stock release policies for times of crisis. Instead, stocks are only supposed to be released when they are abundant (via OMSS releases) but this does not depend on the current supply situation. In contrast, stock policies in China seem to be closer to an optimal policies as substantial amounts were released during 2007 and 2008 (Yang et al. 2008).

The biggest changes in public stocks in recent years seem to be driven by the amount of rice harvested, the export ban policies and in some years by huge increases in the MSP. During the world food crisis in 2007-2008, India's stocks soared due to the MSP increases and the export ban. For example, the mere introduction of the export ban led to a public stock increase of around 2.9 million tons while the 29% increase of the real MSP contributed another 4.8 million tons to the public stocks. It seems, policy makers wanted to protect Indian consumers with the help of these polices but they neglected the impacts on public stocks. These led to dramatic stock increases and thereby huge management costs as well as unnecessary high prices on domestic markets between 2008 and 2012 (even though prices were well below global levels).

Hence, India's buffer stock policy is prone to fail at least one of its objectives, the protection of consumers by preventing high prices. This is a result of the way the stock releases and acquisitions are managed. Stock releases for the PDS are pre-defined and not crisis-responsive. The other channel for stock releases, the OMSS releases, depend on the current stock levels, i.e. stock out happen only when stocks are (substantially) above the norm. Additionally, OMSS releases currently depend on the ability to cover economic costs for the FCI, a policy which urgently needs to be overcome to offer consumer protection. Thus, both channels for stock releases do not respond to high prices, supply shortages, and a crisis in general. Furthermore, the processes for stockpiling as well as stock releases are too slow to be used for quick interventions. Stockpiling reacts to the MSP and the private supply both of which are determined long before the end of the marketing year. Stock outs are mainly carried out through the stable provision of rice for the PDS. However, in times of need, quick and substantial domestic stock releases would be required, in particular, if measures are taken which might increase the ending stocks such as MSP increases or banned exports. Such factors need to be taken into account for future market interventions. For example, a significant raise of the MSP must be accompanied by additional stock releases. Similar stock releases are required if export bans, which may help to stabilize prices via decoupling Indian markets from world markets, are introduced. As noted by Gouel, Gautam, and Martin (2014) a storage policy without clear stock out rules apart from the PDS results in a buy-and-hold strategy. Hence, India's stockholding policy needs to be adjusted to offer crisis-responsive consumer protection, particularly to reach people which are not reached through the PDS.

Unsurprisingly, private stocks are found to be largely crowded out by public storage. However, crowding out is partial as for each ton of public stocks, private stocks are reduced by about half a million ton. These findings indicate that despite the high degree of government interventions, there are still speculative storage activities ongoing in India. These activities contribute to stabilizing prices because the dynamics of the competitive storage model imply a price stabilizing behavior of the stockholders and this behavior was found in the estimation. As crowding out is only partial, the government can increase the total stock levels by holding public stocks. This would allow the Indian government also to use theirs stocks more as an emergency reserve and rely more on private stockholders in "normal" times when supplies are sufficient. However, such an approach would require a fundamental change of the current institutional system. The other main driver of private stocks is the market supply as expected from the theory of competitive storage. Furthermore, private storage reacts to export opportunities, i.e. banned exports or a large surplus in the rest of the world increase the private carry-over stocks.

In general, combining trade and storage policies to stabilize prices may work but the current stockholding system fails to provide the required speed for interventions, the automated channel to releases stocks as response to a crisis, and the means to protect consumers in the short run. Adjustments need to be quicker and more responsive to the market situation, in particular for stock releases. Currently, stock policies cannot protect consumers from fast-onset crises; instead, this was achieved by implementing export bans in the past. Those bans, however, come at huge costs for countries relying in imports. Therefore, storage policies should be adjusted to provide short-term consumer protection and keep fiscal costs in check such that trade can remain unrestricted. Even if incentives to restrict exports in times of a crisis may prevail, better stock release policies would allow more time for evaluating alternative measures and negotiating with the international community. Furthermore, producers and traders are likely to benefit from the unlimited trade (Shreedhar et al. 2012).

Limitations of this study arise from the quality of the underlying data and statistical limitations. The latter are a result of the limited number of observations and the remaining uncertainty about the stationarity of some variables. However, different approaches including estimations on levels and first-differences were used to account for these. If policy changes are made ad-hoc and not based on the usual rules, such effects also cannot be considered. Furthermore, it is assumed that there are no announcement effects.

With clear rules and possibly more reliance on the private sector, India can reduce the fiscal costs of the policies while maintaining a similar level of price stability or food security (compare Basu 2011; Gouel et al. 2014; Saini and Kozicka 2014). Future research should explore more flexible public storage policies, the effects of trade liberalization policies (Anderson and Martin 2005; "Edward" Yu et al. 2011; Hoda and Gulati 2013; Laborde and Martin 2012), and how the private sector could further contribute to stabilize food prices and supplies. As an alternative to the public stockholding program, future research also needs to explore the potential of cash transfer or food coupon scenarios (as in Basu 2011; Ecker and Qaim 2011 (for Malawi, not India); Kozicka et al. 2015a). Finally, interactions between domestic and international markets need to be studied, in particular if uncoordinated policy responses are implemented in times of crisis (von Braun et al. 2014). Taking the results of chapter 3 into consideration, a way needs to be found to align domestic price stabilization policies and international efforts to reduce trade restrictions. Increased support from the international community may be the only way to provide the right incentives for India to keep exports flowing when international supply falls short.

6 Using information: When do Prices Matter Most for China's Grain Supply Response?[20]

6.1 Abstract

Agricultural supply needs to respond to prices in order to prevent food shortages and allow an efficient allocation of resources. Yet, knowledge on the up-to-dateness of farmers' price information is scarce, even for countries like China. This chapter fills this gap by analyzing how the production of indica rice, winter wheat, and corn, China's most important staples, responds to prices at different points in time. At first, a directly estimated single commodity supply response model is set up for the agriculturally most important provinces in China. Then, by evaluating the impact of prices at different points in time, insights can be obtained about how up-to-date farmers' price information is. The difference GMM estimator is used because the number of groups (provinces) is large compared to the time periods and because production response is a dynamic process. Evidence of weather impacts on production is mixed, but high temperatures consistently reduce production which is worrying in view of global warming. All crops are found to strongly respond to prices around and shortly before planting time. Elasticities of prices further away from the time of planting are of lower magnitude and often insignificant, except for wheat because of its long growing period. Prices during last year's harvest time have little explanatory power, which provides strong evidence against naïve or Nerlovian price expectation models. Results could also be used for short-term forecasting if timely input data were available. The presented method of analyzing the timing of the price response may also be used for as a general test for the robustness of a model.

6.2 Introduction

Unexpected high and volatile food prices during the 2007/08 world food crisis and thereafter have reemphasized the need of protection against supply shortages. In view of various trade restrictions imposed by major exporting countries, governments tend once again to focus more on self-sufficiency and food storage. Additionally, in particular emerging economies like China aim to increase their yields due to limited possibilities of expanding agricultural land combined with a rising population, total grain demand and meat consumption.

The primary purposes of studying the supply response are threefold in this analysis. The first aim is to identify the different factors that can affect production, such as market prices,

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biophysical conditions and infrastructures. The second and main objective is to evaluate how the predictive power of prices evolves over time and therefore to understand when farmers react most strongly to prices. This reveals how up-to-date farmers' price information is and how their price expectations are formed. Thirdly, differences between the crops are analyzed. Hence, a clear understanding of the farmers' planting and production behavior is needed.

Farmers' decision-making is generally modeled as a two-step process (Colman 1983): First, farmers choose the crop type based on past weather conditions and decide their cropping area based on the prices they expect to receive several months later. Second, after planting, they change their farmland management measures according to market prices and weather condition to achieve a high yield. This study focusses on the production response of winter wheat, indica rice, and corn as these crops are the main staple foods in China. The country is the biggest producer of rice and wheat and one of the biggest producers of corn. The results of this research can also be used as the basis for a short-term forecasting tool for monitoring Chinese food security or as part of a worldwide food availability monitoring tool. However, forecasting would require timely availability of data, which usually is not possible for data from the Chinese Agricultural Yearbooks.

In China, early works in this field have focused on the roles of price and marketing reforms in agricultural production (e.g. Lin 1991). Empirical studies have found a positive impact of prices on output during the first years of reform (Huang and Rozelle 1996; Lin 1992). Lin (1992) found that 15% of output growth in 1978-1984 came from the rise in relative prices. Huang and Rozelle (1996) showed about 10% of rice output growth between 1978 and 1984 was caused by price effects. The gains have also resulted from increased allocative efficiency through market liberalization since the early 1990s. For example, de Brauw et al. (2004) found that increasing marketization had a positive effect on crop allocation and productivity. The recent works have paid more attention to the impacts of subsidizing agriculture after China shifted its agricultural policy from taxing farming households to providing them with subsidies in 2004. While these subsidies are given to all producers and are very high, even higher than in the US and the EU on a per unit area basis in 2012, they are quite low on a per household or per farm basis as farms in China are mostly of small scale (Huang et al. 2013). Except for subsidies for machinery, which influenced the purchase of machineries, most other subsidies for grain, input, and seed were found not to influence farmers' area allocation decisions (Huang et al. 2011). This finding provides the rationale for not explicitly including subsidies in this study. Increased grain outputs in the later years were partly attributed to land reallocation to grain production (Yu and Jensen 2010). With the help of a dynamic panel approach, acreage and yield responses to output prices were analyzed in a case study for Henan (Yu et al. 2011). Both area and yield were found to be price-responsive. However, evidence from other provinces is missing, and the effects of high temperatures have not been addressed. This analysis focuses on both of these issues. Furthermore, the role of prices at different points in time is at the heart of this study. At the global level, price volatility and therefore price risks were found to reduce the supply response (Haile et al. 2016b). However, as prices are comparably stable in China, price volatility is not considered as an important factor in this study.

Earlier studies which investigated the price building process of farmers have often focused on industrialized countries (e.g. Fisher and Tanner 1978; Holt and McKenzie 2003). Economic theory (Moschini and Hennessy 2001) and applied micro-level studies (Haile 2015) have underlined the importance of price information on production decisions. However, evidence from China, one of the most important countries for agricultural production, is missing and the question to prices at which point in time the aggregated supply can still respond has largely been neglected.

In the face of climate change, interest in impacts of global warming on agriculture is increasing. The impacts of climate change are expected to be huge and have already been partly documented. The general findings include an expected decline of crop yields in China, as in other developing countries (Tao et al. 2006). By employing farm-level data and the Ricardian method, the average impact of higher temperatures was found to be negative, whereas the average impact of more rainfall was found to be positive (Wang et al. 2009). Overall, weather conditions, market prices and infrastructures can be seen as the three most important conditions for agricultural production. This study makes an important contribution to evaluating how such weather-related variables, especially high temperatures, affect the production of the considered crops at the province level. Furthermore, to the author’s knowledge, this is the first study which addresses the production response to prices at different periods in time in order to analyze the aggregated farmers' price expectation formation process for China.

The remainder of this chapter is structured as follows: Sections 6.3 presents the data and explains how data of different frequency and scale was combined. Section 6.4 explains the methodology, first for the general supply response model specification and afterwards for testing the impacts of prices at different points in time. The results are successively presented in section 6.5 before section 6.6 concludes.

6.3 Data description and usage

Data on acreage, production, output market prices, procurement prices, fertilizer prices, rainfall, consumer price index (CPI), irrigated area, temperatures, sunshine, effective irrigated area, and prices of competing crops is obtained from the Chinese agricultural and statistical yearbooks from 1996 to 2012. Province-level data is used whenever possible, but whenever such data is scarce, national-level data is used instead. Own crop prices are deflated by the CPI; other prices are deflated by the own crop price, resulting in relative prices to take into account any possible correlation. Table 6.1 provides an overview of the aggregation level, frequency, and transformations of the data. The summary statistics of the variables are presented in Table 6.2 for the individual crops.

A panel data set is created for each crop, whereby the province-wise production of a crop is used as the dependent variable to be explained by the other variables[21]. The provincial production data, obtained from the National Bureau of Statistics of China, is collected from 1995 to 2012 and includes information on 20 provinces planting winter wheat, 29 provinces planting corn, 13 provinces planting early and late indica rice and 15 provinces planting middle indica rice. For indica rice, data from the early, middle, and (double) late seasons are pooled together to get more observations and hence ensure that the number of observations does not fall below 249. However, this comes at the cost of not being able to detect any heterogeneity in the response which could not be captured by the fixed effects.

The planting season, and complementing and substituting crops may differ slightly among the different provinces. For winter wheat, the planting season is from September to October, and its harvesting takes place in the late April or May of the following year. The main substitute is rapeseed, followed by cotton, while corn is a complementing crop. Corn is mainly planted from April to June and harvested between August and October. The main substitutes are soybean and cotton, and the main complementing crops are wheat and rapeseed. Based on the farmers' production behavior, the focus lies on input and output prices, weather conditions and infrastructure. For crop prices, monthly wholesale prices are used. This is because wholesale prices are more easily available than farm gate prices and also because of the high transmission from wholesale to farm gate prices, as reported in the literature (Liu et al. 2012). Two different definitions of substitution crops have been tested. First, only the relative price of the main crop which serves as substitute was tested and this is presented in the tables. Second, an index of the relative prices of all important crops which serve as substitutes was constructed and tested. As this index turned out negligible, the results are not included.

As land and labor are limited, planting behavior can be affected by the price of competing crops. Fertilizer prices are chosen as the main input market price. Wages, obtained from Bloomberg, are also included, but their time series is short and as a result so is the number of observation. Due to this and the fact that they turn out insignificant, they are not reported in this study but are available upon request. The agricultural production system is sensitive to weather effects, and there are very few measures available to farmers to compensate for weather effects. Therefore, weather conditions, collected from the National Meteorological Information Center of China, are a very important independent variable in this analysis. The

[21] Here, the total production is investigated. Splitting the production up into the area and yield would require more data but allow additional insights. However, endogeneity problems arise as the two variables are not independent.

percentage share of cultivated area under irrigation can also be seen as a measure of infrastructure and technology. Missing values for this variable, but not for any other variables, are imputed. Irrigation also allows farmers to compensate for insufficient rainfall and partly even droughts. As irrigation is typically used in combination with the application of chemical fertilizers, it represents a higher standard of agricultural infrastructure. However, irrigation relates to the cultivated land area under irrigation and hence is not crop specific. As a result, only very limited conclusions can be drawn about how irrigation affects production. This is discussed further in the results section and also applies to the non-crop-specific drought area.

Table 6.1: Overview of the data used for the regression analysis.

Data	China … yearbook	Scale	Frequency	Transformation
Production	rural statistic	Province	Yearly	Logged
CPI	statistical	Province	Monthly	Continuous CPI build from yearly changes
Total farm crop area	rural statistic	Province	Yearly	-
Irrigated area	water conservancy	Province	Yearly	Divided by total farm crop area and logged
Non-Irrigated area	-	Province	Yearly	log(1-irrigated area/total farm crop area)
Wholesale prices	grain	National	Monthly	Divided by continuous CPI and logged (for competing crop prices: divided by own crop price)
Fertilizer prices	price	National	Monthly	Divided by wholesale price and logged
Rainfall	water conservancy	Province	Monthly	logged
Hours of sunshine	1	Province	Monthly	logged
Lowest temperature	1	Province	Monthly	-
Average temperature	1	Province	Monthly	-
Highest temperature	1	Province	Monthly	-
Area affected by drought	water conservancy	Province	Yearly	Divided by total farm crop area and logged

Notes: Own illustration. The second column shows the source, i.e., from which of China's yearbooks the data is taken. 1 means that it is not taken from any yearbook but from the National Meteorological Information Center of China.

As some of the weather data has a high level of autocorrelation, it is not possible to consider every month in the econometric analysis. Therefore, only the most important month is included; except for rainfall, where the sum of the most important months is calculated. The hypotheses to test in this study are as follows: (1) A positive response to own output prices, and a negative response to competing crop prices as well as fertilizer prices, at least if the crop has higher fertilizer requirement than competing crops; (2) own output prices matter most in the time period from shortly before to a few month after planting, during which farmers make their decisions on areas and yields; (3) droughts and insufficient rainfall have a negative effect on production; (4) irrigation has a positive impact and can reduce the negative impact of insufficient rainfall or high temperatures.

Table 6.2: Summary statistics of the data from all provinces

Variable	Obs	Mean	SD	Min	Max
Corn					
Production (1000 tons)	552	458.7	549.5	0.9	2675.8
June WSP (CNY/kg)	463	1.4	0.4	0.9	2.3
Irrigation (1000 ha)	552	1813.9	1385.8	144.2	5205.6
Rainfall@growing (cm)	534	14.1	6.8	1.5	40.4
Average Temp@growing (°C)	534	24.9	3.3	13.2	30.7
Drought area (1000 ha)	495	448.1	544.2	1.0	3133.0
Fertilizer price (CNY/kg)	492	1916.4	672.6	1186.0	3140.0
Winter Wheat					
Production (1000 tons)	360	464.3	686.8	0.2	3177.4
March WSP (CNY/kg)	301	1.5	0.4	1.0	2.2
April's sunshine hours	360	5.6	1.8	1.7	9.4
Irrigation (1000 ha)	360	2041.9	1466.8	173.6	5205.6
Rainfall@growing (cm)	360	6.0	4.8	0.2	22.4
High Temp@flowering (°C)	360	26.0	4.1	16.6	37.3
Rainfall@planting (cm)	360	2.9	1.6	0.1	11.7
Drought area (1000 ha)	321	399.5	482.9	1.0	2573.0
Fertilizer price (CNY/kg)	320	1897.8	665.3	1184.0	3000.0
Indica Rice					
Production (1000 tons)	707	406.1	433.0	0.0	2161.1
WSP@planting (CNY/kg)	594	1.5	0.4	0.9	2.5
Sunshine hours@planting	707	5.4	1.4	2.1	10.4
Irrigation (1000 ha)	707	1751.3	985.5	169.9	3929.7
Rainfall@growing (cm)	707	11.4	4.3	2.6	26.2
Rainfall@planting (cm)	707	3.8	2.6	0.1	19.5
High Temp@growing (°C)	707	33.7	2.0	27.2	39.7
Drought area (1000 ha)	639	292.9	361.0	1.0	2250.0
Fertilizer price (CNY/kg)	632	1867.1	668.0	1126.0	3340.0

Notes: Own illustration. Data which is only available on a national basis is copied for all provinces and therefore is shown to have more observations than it actually has on the national level. Data is only reported if the value for production for that crop, year, and province is available. Unless the month is indicated, the @ is used to specify time periods.

This approach has some limitations. The biggest limitation might be the aggregation level of data. Some price data were only available at a national level, but as price transmission within China is high (Huang and Rozelle 2006), this might not be a concern. For the biophysical variables, even though they were available at the provincial level, this aggregation might be more problematic as rainfall, hours of sunshine, and temperatures may vary in different parts of the same province. Therefore, the influence of these biophysical variables is likely to be underestimated due to this high level of aggregation. Furthermore, important variables may not be considered which could be an issue if they fluctuate a lot in the short term. If instead they mostly consist of a long-term trend, then they will be captured by the orthogonal deviations and lagged production and, as a result, will not cause any problems. Therefore, mechanization and modernization of agricultural practices should not be a concern as long as they happened sufficiently smoothly.

6.4 Methodology

Following Colman (1983), agricultural output supply response analyses can be classified in the following two main categories: programming and econometric models. The econometric approach can be further subdivided in two-stage procedures, directly estimated supply systems, and directly estimated single commodity models (ibid.). The different approaches come with different advantages and shortcomings. Programming models are based on the behavior of individual, representative farms which are then aggregated. Therefore, programming models allow fully accounting for the relationships between different inputs and outputs as well as incorporating constraints on resources, crop rotation, and other variables (compare e.g. Heckelei 2002). In econometric two-stage procedures, output response relationships are calculated by imposing profit maximization marginal conditions on results obtained by econometric estimations in the first stage. This approach makes use of the principles of duality, i.e. the equivalence between the production and cost, and production and profit functions, any of which can be estimated in the first stage (Colman 1983). The third approach, directly estimated supply response systems, estimates an aggregate production function of different products. Therefore, the fixed inputs are allocated to the production of products such that the profits are maximized. However, all of these three methods have the major shortcoming that they suppress the dynamics of supply response and instead provide static outcomes (ibid.). Therefore, they are useful to investigate interactions between products and to evaluate impacts of policies on the agricultural sector. However, they are not useful for forecasting purposes and for determining the supply response over time during the marketing year (ibid.). Hence, the fourth approach is chosen in this study, i.e. directly estimated single commodity supply models. Single commodity supply models are also appropriate for the purpose of this study because only three of the various crops grown in China are considered and these crops are only partly substitutable as they are often grown on different plots. Rice, for example, needs much more water than corn and wheat and is therefore rarely substituted by these crops. Finally, the other econometric models reduce the degrees of freedom in the estimation due to the imposed restrictions resulting from the substation of inputs and outputs. All these factors justify the choice of a direct single commodity supply model.

The expected prices at harvesting time constitute a crucial factor for the production decision. But these prices depend on the specific expectation building process. Under naïve expectations, farmers would assume that the prices at upcoming harvesting time equal those during last year's harvesting time. The Nerlovian price expectation model (Nerlove 1979) assumes that farmers have adaptive expectations and prices follow a cobweb logic where fluctuations are driven by expectation errors. In this model, prices during the planting time do not convey more information than prices during the last harvest but farmers revise their expectations based on past errors. Both of these approaches ignore that price expectations by different actors can influence future prices (Nickell 1985). Finally, there are rational expectations[22] (Muth 1961) which assume that the farmer makes the best use of all available information, i.e. they use all available information to correctly calculate the time-dependent probability distributions of all relevant variables. Within this framework, farmers would incorporate the latest price information in their decisions because these prices convey more information about the current supply and demand situation than earlier prices. With some limitations, the framework adopted in this study allows investigating the appropriate price expectation model for the aggregated supply response of all farmers by testing the impact of prices at different points in time. Hence, it can be derived whether farmers use naïve expectations, Nerlovian expectations, or a somewhat more sophisticated expectations model such as the rational expectation model. However, because no "optimal" production levels are calculated, it cannot be concluded whether farmers actually apply fully rational expectations.

Strictly speaking, a farmer's decision making process consist of two steps: the area decision and the yield decision (Colman 1983). The considered determinants are mostly the same but may differ slightly as, for example, competing crop prices are not that important after the area decision is made. However, they still may be important because they may affect how farmers allocate their inputs such as fertilizers, pesticides, and water, and other variables. On the other hand, not all variables which influence yields also matter when allocating the area. Unexpected rainfall shocks (or price shocks) cannot be anticipated if they occur after planting the crop. Therefore, they cannot affect the area decision. However, these shocks may affect a farmer's fertilizer application and therefore yield. Therefore, modeling production implies modeling a combination of the area and yield processes. Nevertheless, it is important to see the combined effects as the total production volume matters and the aim is to reveal which variables have an influence and how they impact the production. Another reason to look at the combined effect on production is that statistical issues arise when looking at area and yield separately. This is because area and yield influence one another, and therefore this additional endogeneity has to be dealt with. For example, area allocation decisions may affect yields in two different ways: High prices could cause farmers to favor large planting areas, which

[22] There are also variants of quasi-rational expectations, compare e.g. Holt and McKenzie (2003).

should increase the expected yields, whereas planting area expansion may negatively influence yields if the additional crop areas are located on less-productive lands. If models only model the area decision, their forecasting precision for the production volume is limited. If they model both decisions, they have to account for this endogeneity which requires a very high number of observations such that appropriate models can be applied.

The production quantity y_{lit} of crop l in province $i \in [1, \dots, N]$ in period $t \in [m + 2, \dots, T]$ is estimated according to

$$y_{lit} = \beta_0 + \sum_{e=1}^{m} \sum_{s} \beta_{lse} w_{lsi,t-e} + \sum_{k=1}^{n} \sum_{j} \beta_{ljk} x_{lji,t-k} + \lambda_{lt} + \eta_{li} + u_{lit} \qquad (6.1)$$

where the all β's are the coefficients to be estimated, w_s's are the predetermined covariates which are potentially correlated with past errors (lagged production), and x_j's are the independent variables (prices, rainfall, temperatures and other included exogenous variables as explained before). The sums over e and k capture the lagged values of the corresponding variables. The lag lengths m and n are assumed to be sufficient to ensure that u_{lit} is a stochastic error (compare Roodman 2009). Time dummies are represented by λ_{lt}, the unobserved individual effect by η_{li}, and the observation-specific errors by u_{lit}.

The Arellano-Bond difference GMM and system GMM estimators (Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998; Holtz-Eakin et al. 1988) are applied in this study. They are appropriate for a number of reasons. First, the time period is rather short, usually around 14 years, while the number of observations per time period is comparatively large: 20 for wheat, over 29 for corn, and around 40 for rice. The difference GMM and system GMM estimators control for such dynamic panel bias. Second, the production response is a dynamic process, i.e., current realizations depend on past ones. Third, fixed effects allow for heterogeneity across groups, namely provinces. Last, idiosyncratic disturbances may have individual-specific patterns of heteroscedasticity. Thus, equation (6.1) is transformed into first-differences for the difference GMM estimator.

For all three crops, four different specifications are shown in the tables in the results section, with the first three presenting different control variables for the difference GMM estimator and the fourth illustrating the results for the last specification using the system GMM estimator for comparison and robustness checks. While including more variables allows controlling for more factors, it also decreases the degrees of freedom, the significance of variables which are correlated, and, most importantly, the number of observations (because many variables are only available for a limited number of years). Comparing the different specifications and comparing the difference and system GMM results provides a further consistency check. In general, it seems that the difference GMM estimator is more appropriate as it cannot be ruled out that the first differences of the instrument variables are uncorrelated with the group fixed effects. Findings support this hypothesis, as will be shown in the next section. The Windmeijer finite-sample correction for standard errors is used (Windmeijer 2005). The xtabond2 command in Stata is used, which was written by David Roodman, and followed the application guidelines in his accompanying paper (Roodman 2009). Instead of first differencing, forward orthogonal deviations are used (Arellano and Bover 1995; Roodman 2009), i.e., the average of all available future observations was subtracted. This procedure removes fixed effects, just like differencing, but because lagged observations are not used, these remain orthogonal to the transformed errors. This way, the number of observations will not be reduced by gaps in the dataset. As suggested (ibid.), time dummies for all years are included in all model specifications.

For proper usage of the GMM techniques, a number of test need to be run to check the consistency of the estimations (ibid.; Efendic et al. 2009). The joint significance of the variables is evaluated with an F-Test, the p-value of which is expected to be clearly below 0.1 (ibid.). While the first lagged residuals are expected to be correlated, the twice lagged residuals must not (Arellano and Bond 1991). Considering the null hypotheses, this means the p-value of the AR1 test in the result tables is expected to be smaller than 0.1, while the p-value for the AR2 test should be higher than 0.1 (for significance at the 10%-level). Furthermore, the Hansen-J test allows checking if the model specification and all over-identifying restrictions are correct (Baum 2006). It is suggested that the p-value should be above 0.25 but at the same time should not perfectly match 1 for this test (Roodman 2009). The difference-in-Hansen test is used to investigate the exogeneity of instruments. The null hypothesis is that they are exogenous. Hence the respective p-values have to be above 0.1 in order to not reject the null hypothesis. The number of instruments is chosen to provide robust test statistics. There are no clear rules about the appropriate number of instruments. However, the number of instruments should always clearly be lower than the number of observations, which is the case for all specifications. Furthermore, the coefficient of the lagged endogenous variable (production in this case) should be less than one to obtain a steady state behavior (Roodman 2009), which is the case in all of the presented models. Finally, the validity of the estimates can be verified by examining if the coefficient of the lagged dependent variable is larger than the one obtained by a fixed effects model and smaller than one obtained by using OLS (Bond 2002). This is the case for all specifications and the FE and OLS estimates of the lagged dependent variables are reported in the tables.

All the test statistics are fulfilled in all specifications except for two instances: (1) the first specification for winter wheat, which fails to reject the second order autocorrelation at the 10% level but nevertheless does so at the 5% level; and (2) the first specification for indica rice, which fails to reject the Hansen-J test and the difference-in-Hansen test.

Apart from evaluating the production response using the price at a predetermined point in time, this work aims at analyzing how production responds to prices at different points in time. Therefore, the regressions are conducted with prices at different months before and after planting, from 20 month before up to 20 month after planting, and how this changes the results is graphically illustrated. For this analysis, the second specification is used for all crops as this specification provides the maximum number of observations while fulfilling all test criteria and while including the most important variables. This procedure allows us to analyze how farmers build their price expectations and how up-to-date their price information is. It is not possible to fully distinguish between the two with the presented method. If prices during the last harvest were the most relevant, it would remain unclear whether farmers do not have up-to-date price information or whether they just do not use them because they rely more on the harvest time prices. However, as it is found that farmers use the latest prices for they production decision, it is clear that they be informed about the latest prices and also take them into consideration. Under the assumption of efficient markets, the latest prices incorporate all available information about supply and demand and therefore it is economically makes sense to use these information rather than old harvest time prices.

For indica rice, data for the three different seasons are pooled together. Hence, there is no fixed planting month, but the appropriate planting month is chosen depending on the season instead. All the other variables were similarly chosen relative to the month of planting for that season. This means, for example, that the planting time price is April for early indica, May for middle indica and July for late indica rice. Similarly, rainfall during the growing season refers to April and May for early indica, May and June for middle indica, and July and August for late indica rice.

All variables are logged, and therefore the effects can be interpreted as elasticities. The only exceptions are temperatures, which also exhibited negative values and are more intuitive to interpret in their non-logged form.

6.5 Results

6.5.1 Basic regression results

The results for the production of corn are shown in Table 6.3, for winter wheat in Table 6.4, and for indica rice in Table 6.5. The first row always shows the lagged production. Wholesale prices are denoted by WSP followed by the month or relative time period. The latter are always denoted by the @ symbol and refer to the planting, growing, flowering, or harvesting season of the crop. Average and high temperatures are written as A-temp and H-temp respectively. Interaction terms are indicated by an X, while the prices of competing crops are presented as substitute. The bottom part of the tables shows which estimator was used; the test statistics; and the number of groups, instruments, and observations.

The results for corn, illustrated in Table 6.3, show that all specifications seem to be valid based on the provided test statistics. A significant amount of variation in production can be explained by the previous year's production (which also takes into account unobserved variables). The coefficient ranges from 0.772 to 0.956 and are significant at the 1% level in all specifications. The wholesale price in June turns out to be also always highly significant and have a major contribution, as evident in its elasticity of around 0.2. This implies that a 1% increases in prices will lead to a 0.2% increase in production, which seems reasonable and is comparable to the results obtained by similar studies. The fraction of irrigated area is only significant in two specifications but has a huge impact in both. However, it is only significant for the difference GMM specifications that included the interaction terms, which could possibly be attributed to collinearity in these variables (their correlation coefficient is -0.79 for corn, -0.17 for wheat, and -0.46 for rice). In addition, the total effect of irrigation is the elasticity of irrigation plus the interaction term of irrigation with the average temperature. The interaction term takes the value of -20.69 at the sample mean for the second specification, resulting in a combined marginal effect of -0.59. Despite corn needing rainfall during the growing season, the rainfall variable does not seem to have any significant effect on the corn production. However, corn needs little water compared to other staples and in particular vegetables. As mentioned in section 6.3, the irrigation variable measures the total cultivated area under irrigation. This may be a bad proxy for the actual irrigated crop areas; in particular, it is not a measure of crop-specific irrigation. Furthermore, the quality of irrigation is not reflected in this variable. In addition, considering rainfall variability and water availability, the quality of irrigation may change drastically over time. Therefore, the influence of irrigation can only be approximated, and thus it is unsurprising that no effect is found in many of the specifications (when compared with wheat and rice).

High average temperatures during the growing season, which is in mid-summer, have a small but significant negative impact. When interacted with the non-irrigated area (i.e., the fraction of the agricultural area which is not irrigated) it is found that rainfall during the growing season becomes significant. As expected, rainfall has a positive influence on production, albeit a small one. When interacted with irrigation, high average temperatures are negative and significant for the difference GMM specification. This differs from the expectations but might be explained by the imprecise approximation of irrigation or by high temperatures offsetting the benefits of irrigation. As expected, the drought area has a significant and negative influence in all but the system GMM specifications.

High fertilizer prices at planting time reduce the total production; again, this effect seems to be more pronounced in provinces with a high share of irrigated area. This may be attributed to the fact that levels of fertilizer application are usually much higher on irrigated areas, which may therefore be over-proportionally affected. Prices of competing crops turn out to be insignificant, despite testing various ways of including them in the analysis, such as using the province-specific main competing crop only or a weighted average of competing crops.

Table 6.3: Results for corn production response

	(1)	(2)	(3)	(4)
Lagged Production	.807***	.772***	.902***	.956***
	(.166)	(.143)	(.139)	(.034)
WSP June	.296***	.291***	.226***	.177***
	(.077)	(.055)	(.065)	(.05)
Irrigated	-.115	20.1**	16.8**	1.61
	(.131)	(8.12)	(8.07)	(6.65)
Rain@growing	-.059	-.013	-.076	-7.4e-03
	(.063)	(.06)	(.08)	(.033)
A-Temp@growing	-.029*	-.095***	-.058*	-.014
	(.015)	(.026)	(.029)	(.024)
Drought area	-.032***	-.033***	-.035***	-.014
	(8.6e-03)	(9.1e-03)	(.01)	(.013)
Non-Irrigated X		.077*	.071*	.066***
Rain@growing		(.045)	(.037)	(.021)
Irrigated X A-		-.067**	-.052*	-5.3e-04
Temp@growing		(.027)	(.027)	(.023)
Fertilizer@planting			-.203**	-.231***
			(.074)	(.065)
Irrigated X			-.182**	-.191***
Fertilizer@planting			(.068)	(.058)
Substitute@planting			.018	6.3e-03
			(.027)	(.017)
Constant				6.29
				(6.9)
Estimator	difference	difference	difference	system
Groups	29	29	29	29
Instruments	27	29	28	30
p:F-Test	1.7e-19	1.3e-23	1.1e-27	4.0e-37
p:AR1	1.5e-03	1.1e-03	9.9e-04	3.2e-04
p:AR2	.919	.685	.949	.581
p:Hansen-J	.291	.326	.286	.535
p:Diff-Hansen	.812	.9	.436	1
OLS	.988	.991	.985	.985
FE	.741	.683	.747	.747
Observations	384	384	296	325

Notes: Own illustration. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01
WSP=Wholesale price; X indicates interaction terms; H-Temp=high temperature; columns 1-3 are specifications using the difference GMM estimator; for comparison and robustness checks, the results of the last specification are also shown for the system GMM estimator (4).

Table 6.4: Results for winter wheat production response

	(1)	(2)	(3)	(4)
Lagged Production	.951***	.951***	.96***	.964***
	(.104)	(.11)	(.087)	(.063)
WSP March		.338***	.292**	.255*
		(.116)	(.132)	(.143)
H-Temp@flowering	-.043***	-.044**	.061	-.037
	(9.6e-03)	(.019)	(.123)	(.122)
Sun@flowering	.156	.081	.124	.196
	(.092)	(.205)	(.207)	(.293)
Rain@planting	.054**	.045	.04	.047
	(.021)	(.026)	(.042)	(.037)
Rain@growing	3.5e-04	-.045	-.143	-.133
	(.032)	(.037)	(.099)	(.091)
Irrigated	-.055	-.344	-31.9	-.093
	(.483)	(.478)	(37.2)	(26.4)
Drought area	-.037**	-.026	-.034	-.026*
	(.014)	(.016)	(.02)	(.014)
Non-Irrigated X Rain@growing			-.137	-.177
			(.135)	(.165)
Irrigated X H-Temp@flowering			.105	-1.1e-03
			(.125)	(.089)
Constant				10.3
				(36)
Estimator	difference	difference	difference	system
Groups	20	20	20	20
Instruments	26	25	27	29
p:F-Test	1.4e-13	2.0e-12	2.0e-14	1.8e-22
p:AR1	8.8e-03	.019	.012	.016
p:AR2	.053	.185	.173	.241
p:Hansen-J	.595	.463	.805	.744
p:Diff-Hansen	.949	.847	1	1
OLS	1.01	1.02	1.02	1.02
FE	.865	.855	.863	.863
Observations	280	249	249	269

Notes: Own illustration. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01 WSP=Wholesale price; X indicates interaction terms; H-Temp=high temperature; columns 1-3 are specifications using the difference GMM estimator; for comparison and robustness checks, the results of the last specification are also shown for the system GMM estimator (4).

For winter wheat, the previous year's production is again the most important driver and consistently significant at the 1% level (Table 6.4). Wholesale prices in March have a similar positive and significant effect, as for corn. The elasticity is around 0.29, even slightly higher than for corn. The first specification does not include any prices to ascertain if there are any changes when more observations are included. This is because the number of observations for winter wheat is relatively low compared with corn and rice. The amount of sunshine at flowering (around two month before harvesting) is insignificant. From the literature, wheat is expected to require much sunshine during this period (FAO 2015) but the aggregation level may explain the insignificance. Furthermore, much rain is needed during and shortly after planting as well as during flowering and yield formation (ibid.). The positive influence of rainfall during and after planting can be observed in the first specification only. Rainfall during the growing season and its interaction term with the non-irrigated area are always insignificant. This might be a result of data aggregation, as explained above. The irrigated area seems to have no effect, but this may be attributed to the poor approximation of irrigation, as explained above. The drought area has a significant negative impact in two specifications, again albeit with a very small effect. The expected negative effect of overly high temperatures during flowering time vanished once the interaction term with irrigation is included. Then, both terms become insignificant. Fertilizer prices and prices of competing crops have no significant effect but reduce the number of observations substantially. Therefore, they are not shown separately but are available upon request.

Similar to corn and wheat, lagged production is the most important driver of indica rice production (Table 6.5). The effect of the wholesale price is similar as in the case of corn, it is always significant and has an effect size of around 0.2. Rain during the growing season, a large amount of which is required to flood rice paddy fields, is positive but only significant at the 10% level in one specification. But as explained before, this might be a result of aggregating rainfall data across the provincial level. The results do not change when squared rainfall is included. Even when interacted with the non-irrigated area, the rainfall stays insignificant. The irrigated area itself is insignificant, which, as detailed before, might be attributed to the poor proxy used for irrigation. For sunshine, a 1% increase in the number of hours of sunlight increases the production by around 0.16% in all the difference GMM specifications. Similarly, the damaging effect of overly high temperatures during the growing season can be observed in all difference GMM specifications. The drought area, fertilizer prices and the prices of competing crops all turn out insignificant. The underlying reasons might be that the costs of switching crops from rice are relatively high and that rice needs a comparatively small amount of fertilizer per unit output.

Overall, the results are mostly comparable to other similar studies. In a non-crop specific analysis, Ghatak and Seale (2001) found price elasticities between 0.174 and 0.394, which is similar to findings in this study. Looking only at the national level, own price elasticities of 0.23 for rice, 0.052 for wheat, and 0.164 for corn have been reported (Haile et al. 2016a). The results for rice and corn are comparable, whereas a higher price response for wheat is found. For Henan, Yu et al. (Yu et al. 2011) found no significant response for wheat but a surprisingly high elasticity of 0.737 for corn. However, according to the study, the elasticities of competing crop prices were also high and significant. They also reported that rainfall increased winter wheat production when considering the total effect on area and yield. For corn, they found that rainfall had no effect, which is consistent with results from this analysis if only the non-interacted rainfall is considered – as in the study by Yu et al.

Table 6.5: Results for indica rice production response

	(1)	(2)	(3)	(4)
Lagged Production	.913***	.914***	.778***	.911***
	(.07)	(.055)	(.112)	(.081)
WSP@planting	.196***	.181***	.163**	.241**
	(.067)	(.054)	(.061)	(.094)
Rain@growing	.053*	.152	.115	.425
	(.027)	(.139)	(.178)	(.284)
Sun@growing	.174***	.167***	.142*	.023
	(.061)	(.05)	(.074)	(.117)
H-Temp@growing	-.024**	-.026***	-.039***	.019
	(.01)	(8.5e-03)	(.013)	(.03)
Irrigated		.356	.323	1.06
		(.521)	(.674)	(.731)
Non-Irrigated X		.294	.262	.691
Rain@growing		(.287)	(.346)	(.495)
Drought area		-4.9e-03	-1.4e-03	4.6e-03
		(8.8e-03)	(8.0e-03)	(.012)
Fertilizer@planting			.032	-.048
			(.078)	(.058)
Substitute@planting			.018	.04
			(.032)	(.048)
Constant				-4.51
				(9.08)
Estimator	difference	difference	difference	system
Groups	41	39	39	39
Instruments	20	23	22	24
p:F-Test	2.8e-16	3.2e-20	1.2e-15	1.0e-22
p:AR1	.073	.098	.118	.096
p:AR2	.174	.171	.142	.138
p:Hansen-J	.153	.341	.409	.24
p:Diff-Hansen	.088	.102	.227	.569
OLS	.997	.998	.994	.994
FE	.727	.722	.551	.551
Observations	548	503	394	433

Notes: Own illustration. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
WSP=Wholesale price; X indicates interaction terms; H-Temp=high temperature; columns 1-3 are specifications using the difference GMM estimator; for comparison and robustness checks, the results of the last specification are also shown for the system GMM estimator (4).

6.5.2 Impact of prices on production during the marketing year

As explained in the methodology section, one of the aims of this study is to analyze how production reacts to prices at different points in time. Therefore, the regressions with same specifications are run for prices at different months before and after the planting time. For all other variables, the values used remain the same as before. The results are depicted in Figure 6.1 for corn, in Figure 6.2 for winter wheat, and in Figure 6.3 for indica rice. The figures show the coefficients and the 95% confidence intervals. The statistical significance of the response can then be inferred from the figures. The further the distance between the bars and the y=0 line, the higher the level of significance. If the y=0 line is included in the bars, the coefficient is not statistically significant at the 5% level. The months before or after planting are depicted on the x-axis of the graphs.

Prices far before or after planting do not have much explanatory power for all crops; hence they do not influence production strongly. However, prices around planting time are usually highly significant and, at least for corn and rice, also have the highest coefficient. For rice, prices are significant in a few months far before planting, which may be attributed to the high level of autocorrelation. Nevertheless, both the level of significance and the coefficient increase and reach their highest level around planting time. Both rice and corn have a relatively short growing time – about 2 to 6 months – compared to wheat. This explains why prices during planting period are very important as farmers chose their area and had only little time afterwards to influence yields. Particularly for rice, the beginning of the growing season is highly important and a lack of water during that time cannot be compensated for at a later stage. The finding of a decreased level of significance and a lower coefficients a few months after planting is therefore fully consistent with the expectations. For wheat, the graph looks different: the level of significance as well as the size of the coefficient increase even after planting and reached their highest levels around 6-8 months after planting. This can be explained by the different growing patterns, i.e., wheat grows for about 7-9 months after it is planted. Furthermore, the most sensitive phase of the crop is the flowering and yield formation period, during which the wheat plant is very sensitive to water and temperatures (FAO 2015). This period is around 65 to 15 days before the harvest. As a result, it is crucial how farmers take care of their crops during this time period, while the establishment, tillering, and winter dormancy periods are of minor relevance (ibid.). Considering this, it is expected that prices around six months after planting are very important for the yield. For the area however, prices at planting time should be the crucial factor. Although without making a distinction between area and yield, it is not possible to draw further conclusions about this.

Comparing the different crops, farmers seem to react earlier to corn prices than the prices of winter wheat and indica rice. Rice shows the lowest response to prices, which might be a result of relatively high costs of area reallocation. For all crops, prices remained highly significant for a while after planting. This indicates that not only the area but also the yield responds to prices, regardless whether it is due to fertilizer or pesticide application, irrigation, or other factors. For prices at harvesting time and thereafter, this method suffers from endogeneity problems as it is no longer clear if prices drive production or vice versa. Therefore, this method is only statistically robust for the time before harvesting, even though convincing results are also obtained for the period afterwards.

A clear result of this analysis is that farmers, at least on average, do not mainly take into account previous year's planting or harvesting prices but rather consider current prices around planting time to be the more important. This is at odds with naïve and Nerlovian price expectation models, which use lagged harvest prices for estimating production decisions. Economically, it makes sense to use current prices as they include more information about the demand and supply situation than last year's prices.

Additional graphs which show the significance (p-values) of the supply response over time for all crops and both estimators are shown in the appendix (Figure 8.4 and Figure 8.5). For these and the subsequent graphs, model specification two is used for all crops, and only the prices are varied over time while all other explanatory variables are kept the same. As expected, these graphs show a U-shape curve with more or less distortions depending on the crop and estimator. Figure 8.6 and Figure 8.7 show the same results for corn while also illustrating the results for other variables: Figure 8.6 for the difference GMM estimator and Figure 8.7 for the system GMM estimator. These graphs again support the hypothesis that the difference GMM estimator performs better than the system GMM estimator. The fluctuations of the System GMM results are much higher, particularly for winter wheat and indica rice as shown in Figure 8.5. Furthermore, the fluctuations of the non-price variables are also much higher, as indicated in Figure 8.7. In general, the period up to which prices are significant extends further after planting for the difference GMM, while in the case of winter wheat the period also starts before planting.

Knowledge about public storage operations in China is scarce. However, when global food prices surged in 2007/08, the Chinese government had introduced export restrictions and released public stocks (Yang et al. 2008). This allowed limiting domestic price increases to 4% (Timmer 2010). Therefore, China seems to also follow an anticyclical storage policy which further helps to stabilize prices. However, if exports are restricted, the supply cannot respond to a potential global scarcity and there is a risk that a crisis might develop. In the short run, it may have global impacts but no impacts for China, but in the longer run China will also be affected as the stocks will be depleted at some point. Therefore, given the responsive supply, it would be preferable to allow a certain degree of price increases such that the supply can respond and future demand can be met (argumentation in line with Yang et al. 2008).

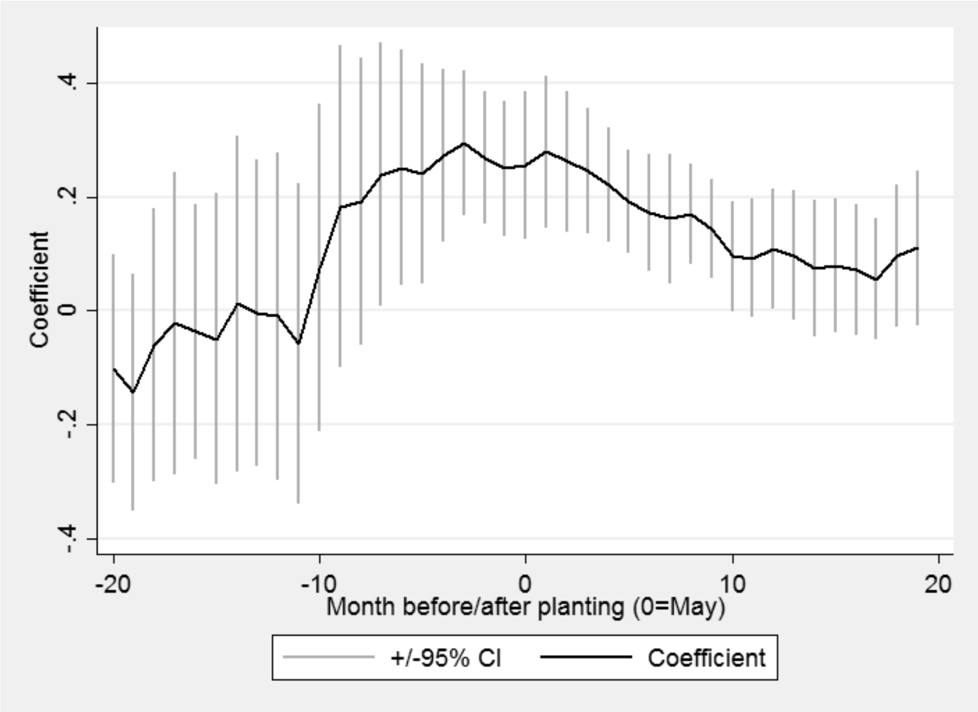


Figure 6.1: Explanatory power of prices over time for corn (Own illustration)

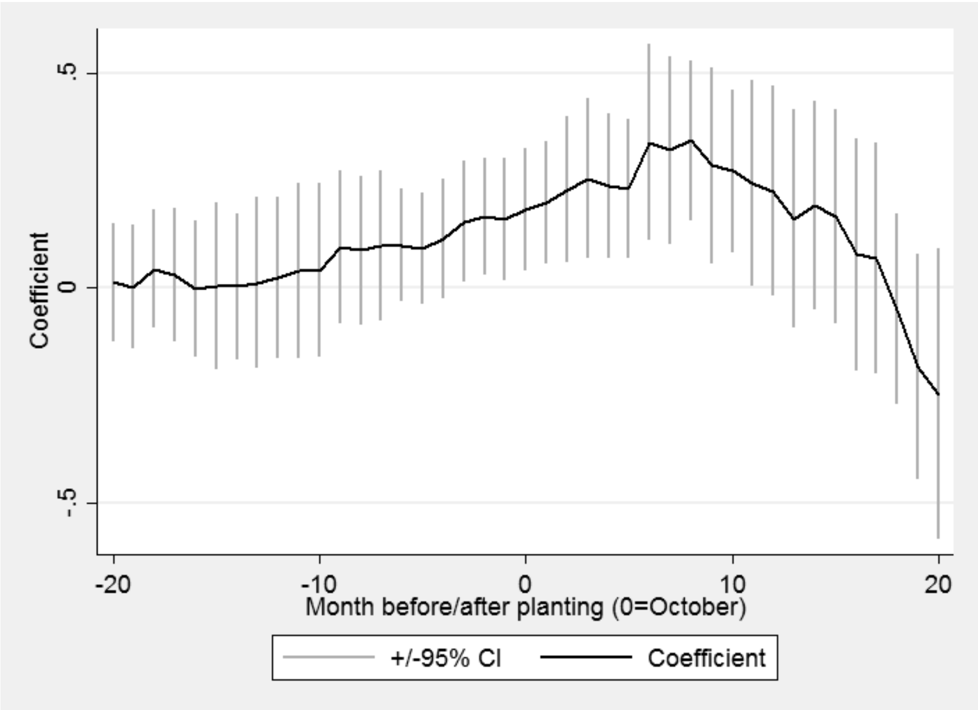


Figure 6.2: Explanatory power of prices over time for winter wheat(Own illustration)

This method of investigating prices at different points in time may also be used for general model specification tests. For a robust model, the significance of the tested variables is expected to consist of low-frequency components, which implies that there are only slow and smooth changes. The occurrence of big fluctuations in a specification, in particular if some variables constantly alternate between being insignificant and significant, suggests that the specification is not robust. Figure 8.5 and in particular Figure 8.7 accordingly indicate that the system GMM specification is less consistent than the difference GMM specification. However, the system GMM fluctuations may still be acceptable; for problematic specifications, much higher fluctuations can easily be observed. Interestingly, prices around two to five months before planting time seem to have such a high explanatory power in the case of the system GMM that all other variables apart from the lagged production become insignificant (Figure 8.7). This is an indication that prices before planting might be the most important factor influencing final production. Examining the area and yield response separately could shed more light on this issue. Overall, the price response and the response to other variables are consistent with the expectations, even though many variables turned out insignificant.

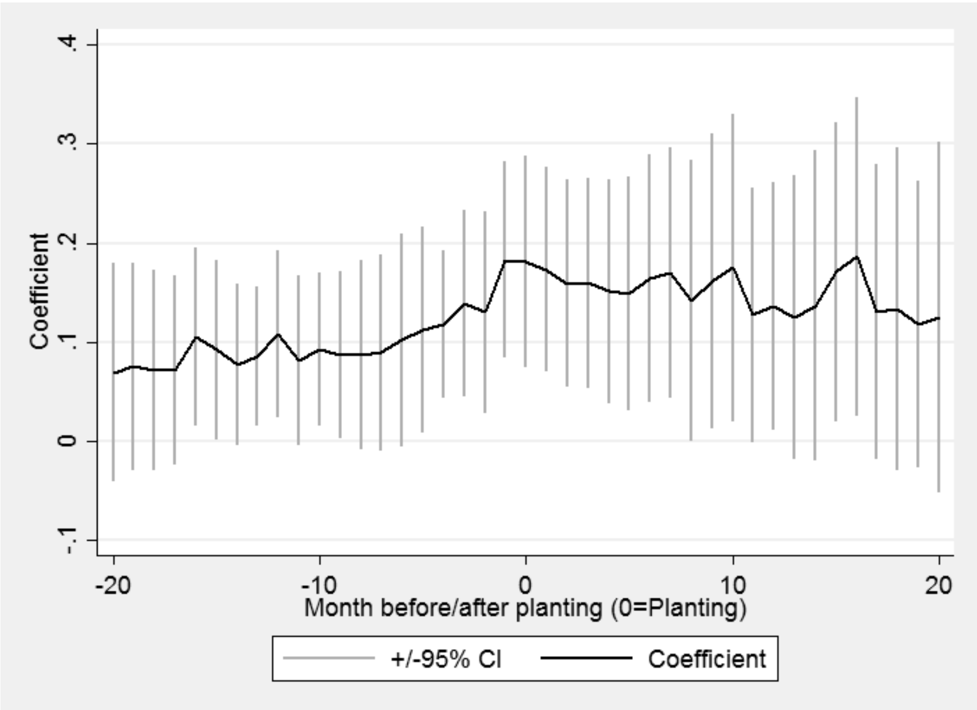


Figure 6.3: Explanatory power of prices over time for indica rice (Own illustration)

6.6 Conclusion

The corn, winter wheat, and indica production response for the main agricultural provinces in China are analyzed using a directly estimated single commodity supply response model which allows investigating dynamic relationships. The difference GMM estimator and, for comparison, the system GMM estimator are applied because the number of provinces is larger than the number of years considered. Apart from testing the impact of different variables such as temperatures and rainfall on the supply response, understanding at which points in time prices matter most for the supply response is a crucial contribution of this chapter. The major findings include the following: (1) All crops strongly respond to prices at planting time and shortly before. This indicates that farmers behave rationally in the sense that they incorporate the latest price information in their decisions. This result therefore provides strong evidence against naïve or Nerlovian price expectation models. (2) The price response of corn and wheat are higher than the one of rice. (3) While prices shortly before and after planting period have very high explanatory power, prices further away from the planting period have lower coefficients and are mostly insignificant. (4) Wheat is an exception in the sense that its prices are highly significant long after planting and show large coefficients, which can be attributed to wheat's long growing period and the crop's sensitivity 1-2 months before harvest. (5) High temperatures negatively influence production for all crops, which may become problematic in the future due to climate change impacts. (6) Irrigation is measured poorly and therefore may have limited the significance of the results; nevertheless the results indicate that irrigation may partly help to mitigate a shortfall in rainfall but cannot (fully) compensate for the negative effects of high temperatures. (7) High fertilizer prices have a negative impact on corn production only.

In general, the difference GMM estimator seems to perform better than the system GMM estimator. The presented method to analyze the importance of prices at different points in time may also be used for general model specification tests if data on explanatory variables is available at a sufficiently high frequency.

The mixed evidence regarding the role of weather events and irrigation in affecting production can be due to the use of province-level data, which might be too aggregated to study spatially differentiated weather impacts. On the other hand, the panel data contains observations over time, which is an important advantage over cross-sectional farm-level data, in particular when studying the role of determinants with little spatial dispersion (such as prices). Studying price impacts on production at different points in time, which is a major contribution of this analysis, can only be undertaken with the help of a panel data set over multiple years. Findings clearly indicate that (overall) farmers have access to and use up-to-date price information when making their production decisions. The month-specific price elasticities also highlight when the Chinese agricultural sector can best respond to price spikes and scarcities. As the price elasticities range from 0,16 (rice) to 0.34 (wheat), increasing domestic demand can be met to a substantial extent by supply expansion – provided that prices are suitable signals about supply and demand conditions. Given the responsive supply, less reliance on public stocks and a reduction of trade restrictions are policy options which should be considered by the government. Otherwise, China may be able to protect itself in the short run with the help of export restrictions and stock releases. But in the longer run, stocks may be exhausted and the supply would not respond to the global scarcity if prices cannot transmit. Therefore, the government should at least allow a certain level of price transmission by not restricting exports too much (argumentation in line with Yang et al. 2008).

The biggest limitation of this study arises from the pooling of provinces which conceals the heterogeneity of provinces. Furthermore, the aggregation of data, mostly on the province level, weakens the results for some variables, including temperatures and rainfall. Coefficients for irrigation and area affected by drought and some other variables were mostly insignificant which could be attributed to the fact that the variables were not crop-specific and therefore only serve as approximations.

Future research should analyze how off-farm wages influence production decisions as off-farm employment options have driven many Chinese people out of agriculture in the past. In addition, climate change impacts on crop choices, yields, and nutritional contents constitute important areas of future research.

7 General Conclusion

Given the severe impacts of high and volatile food prices, this thesis set out to explore the role of public stockholding, private storage, information availability, trade policies, international cooperation, and supply response in stabilizing staple food prices. High and volatile prices can negatively impact production and consumption decisions, drive people into poverty as well as poverty-traps, discourage investments, and lead to social unrest. The risk of global supply shortages persists and regional shortages are frequent. Currently, some countries face severe food shortages induced by the impacts of the ongoing El Niño. Therefore, price and supply stabilization policies are crucial for poor countries and have received widespread attention in academia. Yet, several research gaps prevail and many policies remain a constant source of controversy, particularly those related to public stocks or trade restrictions. Several of these controversies were studied in this thesis using a wide variety of methods including econometric techniques and numerical optimization methods.

Here, the individual chapters are concluded successively. First, the objectives and research questions are restated and findings summarized. Then, the theoretical implications are outlined, i.e. how findings could influence future understanding and application of knowledge of price stabilization. Finally, concrete policy implications are drawn, limitations highlighted, and recommendations for future research specified.

7.1 Chapter 2: how and why global grain supply and demand estimates differ

Objectives, relevance, and findings. Up-to-date information of high quality is important for an optimal resource allocation and accordingly for resilient markets which can absorb shocks. However, knowledge about the quality of global grain supply and demand estimates is as scarce as it is vital. Therefore, the aim of chapter 2 was to *reveal the nature and determinants of differences between the supply and demand estimates from different sources*. To achieve this, cointegration analysis, granger causality tests, and three other methods were used. It was found that sources have similar information sets at their disposal and differences seem to be driven by methodological discrepancies. In contrast to production data, stock and trade data seem to suffer from tremendous uncertainty. Weak evidence suggests that the FAO might be slower than the IGC and USDA in updating their estimates. Additionally, it has been argued that taking the average of the estimates from the three sources may improve the precision and robustness of studies based on this data.

Theoretical implications. Between-source comparisons, as conducted in chapter 2, are scarce and have either focused on the U.S. (e.g. Egelkraut et al. 2002; Garcia et al. 1997) or are outdated, less comprehensive, and less careful in accounting for methodological discrepancies (Paulino and Tseng 1980). Methods presented in this thesis allow numerous insights while accounting for various methodological differences. However, methods to compare data on estimates based on different definitions of marketing years remain yet to be developed. It has been shown that taking the mean value from the three sources provides various advantages over taking the estimates from any specific source. This approach can reduce the impact of mistakes in the data, of estimation errors, and of potentially inappropriate data collection or aggregation methodologies. Furthermore, the mean is expected to be closer to the real value. Therefore, the robustness and precision of results of future studies which are based on global grain supply and demand estimates can be improved by using the average value from the three sources rather than data from any specific source.

Policy implications. Chapter 2 provides various policy implications. First, documentation of data, including collection and aggregation methods, needs to be improved to allow a better understanding of supply and demand conditions. Second, pressure on governments of some emerging economies needs to be augmented in order to increase the amount of information that is collected and the extent to which this information is shared (argument in line with Gilbert 2011b). Third, data should be harmonized between sources and provided in a more disaggregated manner (e.g. public versus private stocks, raw products versus processed goods) which would allow additional insights. Fourth, data consistency needs to be improved, e.g. by applying more appropriate definitions of marketing years. Fifth, data on stocks and trade needs to be improved. Sixth, historical artifacts need to be addressed such as differences in stock estimates for the time when the databases were set up which are now partly carried forward from year to year. Finally, when estimates are updated, more information on the underlying reasons should be provided. Given the responsive supply found in chapter 6, the expected gains in price stability from improved information on supply and demand conditions are substantial. Researchers would benefit from data which better fits their needs.

Limitations. Five methods were applied to account for methodological discrepancies but there may be some unknown differences which cannot be captured by these methods. Furthermore, evidence on some of the results is weak, partly because there are no applicable statistical significance tests available.

Future research. Despite its importance, there is little empirical evidence on how uncertainty in agricultural supply and demand information affects price levels, volatility and the behavior of market agents. Furthermore, more research is needed on the accumulation of information from different sources to improve estimations. As information systems focusing on the nationally aggregated supply and demand conditions cannot draw a conclusive picture of the food availability within a country, the ability of policy makers to respond to a crisis also depends on alternative early warning systems that are in place. These are still scarce in indicators, and how different indicators relate to one another is not well understood.

7.2 Chapter 3: comparing emergency reserves, private storage, and trade policies

Objectives, relevance, and findings. Knowledge of public stockholding policies in an open economy is scarce and previous studies on storage-trade cooperation have ignored private stockholding and a responsive supply, two key features when studying price stabilization. To address this gap, chapter 3 *compared the fiscal costs and effectiveness to stabilize prices of maintaining a public emergency reserve, subsidizing private storage, and strategically using trade policies*. Goals included the evaluation of impacts on price levels, volatility, and extreme events, as well as on the activities of market agents. Furthermore, conditions were established under which international cooperation can be achieved. A partial equilibrium model with rational expectations based on mixed complementarity conditions was used to capture the dynamic interactions between agents. Findings reveal the complementarity of an emergency reserve and private storage. More precisely, while a reserve is much more cost-efficient in preventing extreme prices, subsidized private storage is more cost-efficient in reducing food price volatility. This research also suggests that, contrary to popular belief, a reserve is less market-distorting than subsidizing private storage. Under free trade, benefits of price stabilization policies are shared independently of which countries employ them. Hence, countries need to either cooperate and share fiscal costs, or impose export restrictions when their reserves are touched. Otherwise, a collective action problem arises. If the production variability between the countries differs too much, incentives for international storage-trade cooperation may vanish. The results also showed that high prices as observed during the world food crisis in 2007/08 can be explained by the fact that some countries use public stocks in combination with trade restrictions while others do not intervene into markets. In this case, prices in the latter group of countries can rise well above those which would be observed if all countries would refrain from any type of public intervention.

Theoretical implications. Chapter 3 contradicts earlier findings that report highly market-distorting effects of public interventions compared to market based approaches (e.g. World Bank 2005; Zant 1997). It therefore provides theory-driven support for authors who argued qualitatively for the completion of market-based price stabilization approaches by a well-designed public storage program (e.g. Abbott 2010; Galtier 2014, 2013; von Braun and Torero 2009). Earlier findings on the benefits of risk-sharing with the help of regional grain reserves are supported (Kornher and Kalkuhl 2015; Romero-Aguilar and Miranda 2015). In line with previous studies, results indicate that a public storage program implemented by a single country requires export restrictions to prevent the leakage of benefits into foreign markets (Gouel and Jean 2015). Such incentives to restrict trade yield the collective action problem which has repeatedly been investigated (Bouët and Laborde Debucquet 2012; Gouel 2014a; Martin and Anderson 2011) without providing a concrete solution. In contrast, results show that even compensation payments cannot provide the right incentives if the production variability between the countries differs too much. An international or inter-governmental panel on food and nutrition security (von Braun and Kalkuhl 2015) could potentially increase pressure on governments to limit the use of beggar-thy-neighbor policies and lead the way for mutual agreements on global short-term and long-term price stabilization policies.

Policy implications. Results from chapter 3 indicate that the international community should acknowledge that surplus countries with public storage programs face clear incentives to restrict exports in times of crisis, which is of particular importance for the WTO negotiations. It seems that this collective action problem can only be overcome in two ways; first, by setting up common international stabilization programs (an extension of the proposal from von Braun and Torero 2009) which are unlikely to find a mutual agreement due to diverse interests; second, by introducing compensation payments to which most countries will refuse to commit. A potential second-best option is regional cooperation between countries with similar interests, which, however, limits the potential welfare benefits. Another potential second-best option might be to prohibit export bans but permit flexible export tariffs which enable countries to prevent the export of grains from public stocks to international markets. This is the option that was modelled by the flexible export tariff in chapter 3. An international or inter-governmental panel on food and nutrition security as proposed by von Braun and Kalkuhl (2015) could pressure governments to limit the use of export restrictions and could facilitate agreements which are mutually beneficial. Apart from that, results provide strong support that emergency reserves should receive more attention for their cost-effectiveness in preventing extreme events. As policy makers care about price volatility as well as high prices, a combination of a private storage subsidy and a public reserve may pose an interesting possibility to fight both. Either way, reserves should follow clear rules to prevent influence of interest groups and allow anticipation by market actors. Without any global progress in sight, scaling up WFP activities may provide some protection for the most vulnerable people.

Limitations. Results depend on the model calibration, although it was chosen in a very general way. Therefore, results are not intended to provide specific quantitative guidance on how to set up a reserve for a specific country but rather to illustrate the behavioral characteristics and interactions that need to be considered in the design of policies. A particular but well-designed and promising emergency reserve scheme is used thereby restricting possible conclusions to this (and sufficiently similar) schemes. Private storage may happen for other objectives besides profit-maximization (see discussion in sections 4.7.1 and 5.6) and similarly, other market actors may follow different objective functions.

Future research. Several possible lines for future research emerge from this study. The sustainability of a common reserve depending on the characteristics of participating and non-participating countries is still not well understood. Regional case studies accounting for private storage and a responsive supply, but also acknowledging that trade takes time, should be conducted. These are in particular required for regions where the implementation of a regional reserve is currently being discussed such as in the ECOWAS region (ECOWAS Commission 2012). Further research could investigate pathways which allow overcoming the collective action problem that surplus countries may restrict exports in case of a global crisis. A valuable first step in this direction would be an analysis on whether and (if so) how cooperation on storage can limit the incentives to restrict trade. Impacts of high and volatile prices on nutrition and welfare are still not well understood and require further attention. If the problems related to high and volatile prices become better understood, this would allow the inclusion of more specific objective functions in studies on storage cooperation.

7.3 Chapter 4: deriving and testing a surrogate model for private storage

Objectives, relevance, and findings. Given the numerical complexity of the competitive storage model, chapter 4 intended to answer the question whether *competitive private storage can be approximated by a reduced-form equation and whether this equation can provide empirical support for the CSM*. Starting from the competitive storage model with rational expectations, a surface response methodology was used to derive a reduced-form approximation of competitive private storage behavior. This can be used for direct empirical quantification of stock determinants, high-dimensional modelling exercises, and empirical verification of the competitive storage model, the workhorse in private storage simulations. Non-linear least squares were used to show that the obtained reduced-form private storage equation is highly precise in capturing the effects of individual model parameters. The application to stock data from 32 countries provided for the first time empirical support for the competitive storage model while accounting for actual stock levels.

Theoretical implications. Chapter 4 provides empirical support for validity of the competitive storage model, but uses actual stock levels instead of price distributions as in earlier studies (Cafiero et al. 2011; Deaton and Laroque 1996, 1995, 1992; Miao et al. 2011; Peterson and Tomek 2005). The derived reduced-form private storage approximation offers ample potential for direct econometric quantifications of empirical determinants of private stocks. A first analysis of this type is conducted in chapter 5.

Policy implications. Results from chapter 4 point out that operational stocks sum up to around 19.7% of domestic consumption and therefore need to be subtracted to calculate stock-to-use ratios, a common indicator for market tightness. The strong response of private stocks to trade underlines the need to find multilateral agreements on price stabilization policies. Finally, as stockholders respond to demand expectations, information systems should also improve their demand-side estimates and not only focus on the supply-side.

Limitations. The same limitations as in chapter 3 apply. Furthermore, the tested parameter space is naturally limited and a minor influence of small but prevailing public stocks and other policies in the considered countries cannot be fully ruled out.

Future research. A full empirical validation using the method presented in chapter 4, focusing on a specific country-crop combination and accounting for trade distortions and time-dependent trade costs would draw an even clearer picture of the validity of the competitive storage model and the influence of individual parameters.

7.4 Chapter 5: drivers of India’s rice stocks

Objectives, relevance, and findings. India is home to a huge population of undernourished people and one of the biggest public stockholding programs. Yet, surging stocks and costs call for reforms. Therefore, it is necessary to understand *how policies and market conditions quantitatively impact India’s public and private rice stocks*, which constituted the main research question of chapter 5. A new method to estimate public rice stocks was developed by deriving the impact of individual policies from economic theory. The private stock equation was based on results from chapter 4 which were combined with an instrumental variable approach. Findings underline the huge importance of the minimum support price and trade restrictions on public stocks. Recent stock surges are found to be caused by the real MSP increases, export ban, and bumper harvests in several years. The collapse of the public stock system was potentially only prevented by the large production shortfall in 2009/10, the reopening of borders for rice traders, and the high inflation combined with a stagnant MSP in 2010/11 and 2013/14. Each ton of public stocks is found to crowd out half a ton of private stocks.

Theoretical implications. Chapter 5 is a first application of the methodology developed in chapter 4 to quantify stock determinants. It thereby contributes to the closure of the large research gap on empirical stock drivers and public-private storage interactions. In line with earlier studies, a need for reform is highlighted (Cummings et al. 2006; Landes and Gulati 2004; Reardon and Minten 2011; Saini and Kozicka 2014) and in particular the need for better stock-out policies is underlined (Gouel et al. 2014). Indeed, India provides a good example about how public stocks should not be managed: The dynamical component of stock policies is only producer oriented and provides no crisis-responsive consumer protection. PDS distribution is not responsive to a crisis, only export restrictions are. Additionally, policies are hard to anticipate for the private sector which also suffers under additional legal restrictions. Finally, policy makers themselves seem to be unaware of interactions of their policies which have resulted in stock increases during the crisis. However, even under such regulation and market interventions, private speculative storage activities persist. This underlines that private storage should not be neglected in the analysis of public stockholding policies.

Policy implications. Findings from chapter 5 point out that India's policy makers seem to be largely unaware of the effect of their policies on both public and private stocks. The surge of public stocks and associated explosion of fiscal costs during and after the world food prices was largely self-induced by the increases of the real MSP and banning of exports. Stock-out policies urgently need to be revised to prevent stock surges as well as to offer price-responsive protection for consumers in times of crisis. This dynamic consumer protection is currently only achieved by implementing export bans but high food prices are not associated with stock releases. A fundamental change of the system with a higher consumer-orientation and more transparent as well as responsive stocking policies should be considered and compared to cash transfers (compare Basu 2011; Gouel et al. 2014; Saini and Kozicka 2014).

Limitations. Results from chapter 5 are limited by the quality of the underlying data, in particular on public and private stocks. Statistical limitations arise from the limited number of observations and remaining uncertainty about stationarity, even though different approaches have been used to ensure the robustness of the results.

Future research. Outside of India, empirical impacts of public stocks on private stocks still remain a black box. To a large extent, this also applies to the questions on how policies shape public stockholding. For India, reform proposals have been made and corresponding studies have been conducted, but these are not as comprehensive as required for a major change of the system because, for example, the relationship with other sectors of the economy, which is particularly important for transfer schemes, has often been neglected.

7.5 Chapter 6: price information for China's grain supply response

Objectives, relevance, and findings. China experiences a huge growth in food demand and is still reluctant to rely on imports for its main food crops. Thus, a responsive supply is crucial to prevent food shortages. The aim of chapter 6 was therefore to analyze *how up-to-date the price information of China's rice, wheat, and corn farmers are and what the dynamics of the production response to prices are*. The second focus was to reveal the impacts of weather-related factors thereby shedding light on potential future implications of a changing climate. Therefore, a directly estimated single product model was chosen to capture the dynamic effects. The difference GMM estimator was applied to avoid dynamic panel bias which would otherwise arise as the number of provinces is large compared to the number of time periods. Findings indicate that farmers have the latest price information as they react to prices shortly before and around planting. Only for wheat, prices after planting are still important which can be attributed to its long growing period and the importance of inputs during the last months before the harvest. Furthermore, high temperatures are found to reduce production thus raising concerns regarding future self-sufficiency in view of global warming.

Theoretical implications. Chapter 6 indicates the up-to-dateness of price information of Chinese farmers. Using the latest price information is rational as they convey more information on supply and demand conditions than earlier prices, including those of the last harvest period. Usual seasonal price changes can be anticipated. This finding provides strong evidence against naïve or Nerlovian price expectations (Nerlove 1979), models which have also been criticized by others (Braulke 1982; Leaver 2004; Roberts and Schlenker 2009; Tiffin 2004). Instead, farmers seem to behave rationally in the sense that they consider the latest price information in their decision making.

Policy implications. Results from chapter 6 underline the responsiveness of China's agricultural production which is expected to provide a high resilience against shocks. However, high temperatures are found to lower production which highlights the need to find mitigation strategies for global warming and international agreements to limit climate change. In the short run, China may be able to protect itself from global shortages with the help of export restrictions and releases of public stocks as in 2007/08. However, in the longer run, this prevents the supply from responding to the global scarcity. Hence allowing a certain degree of price transmission through reduced export restrictions may be a more sustainable strategy in the long run.

Limitations. The pooling of the provinces conceals the heterogeneity across provinces but is required to obtain sufficient observations. Aggregation on the province-level and the use of a few non-crop-specific variables weaken the findings for some variables including temperatures, rainfall, and droughts. As a result, some of these variables are insignificant.

Future research. For China, off-farm wages are expected to influence agricultural production due to higher opportunity costs for farmers. Hence, drawing more light on this issue would present an interesting extension to the presented analysis. Separating the area and the yield decision when testing the influence of prices over time would allow an even better understanding of the formation of price expectations and the related resource allocation decisions. The impacts of climate change on crop choices, yields, and nutritional contents, potentially all the way to nutritional outcomes for humans, constitute additional important areas for future research.

7.6 Final remarks

This thesis makes important theoretical and applied contributions to the knowledge of price stabilization, most importantly for public and private stocks, trade policies, and information availability. For this, various numerical optimization and econometric methods were applied.

Given the responsive supply that was found in this thesis, expected price stabilizing effects from improved information on supply and demand conditions, particularly on stocks, are substantial. These would also enhance capabilities of early warning systems for monitoring food security. Apart from access to high-quality information, market integration, e.g. through good infrastructure, is key to enable farmers, traders, stockholders, and governments to quickly respond to changing market conditions and thereby enhance market resilience. Another implication of the price-responsive supply is that export restrictions of surplus countries in times of crisis can be particularly damaging because they lead to lower domestic prices and therefore to lower levels of production. This indirect effect of export restrictions can further amplify the increase of global prices.

Furthermore, in spite of widespread criticism against public interventions, this thesis has demonstrated that well-designed emergency reserves can complement speculative private storage to stabilize prices. India, however, has been shown to provide an example of how public storage programs should not be run: lacking crisis-responsive consumer protection, difficult to anticipate for the private sector, and hardly controllable by policy makers due to conflicting policies.

References

Abbassian, A., 2015. Discussion at the Eight Session of the Global Food Market Information Group. Milan. 19 Oct 2015.

Abbott, P., 2013. Improved Methodology for Estimation of Food Stocks. Consulting report to the Food and Agriculture Organization of the United Nations. http://www.foodreserves.org/wp-content/uploads/2014/03/Abbott-Report-on-stocks-data.docx (accessed 9.15.2014).

Abbott, P., 2010. Stabilisation Policies in Developing Countries after the 2007-08 Food Crisis. OECD. http://www.oecd.org/tad/agricultural-policies/46340396.pdf (accessed 9.11.2015).

Abbott, P., Hurt, C., Timer, W.E., 2011. What's Driving Food Prices in 2011? The Farm Foundation, Issue Report. https://www.farmfoundation.org/news/articlefiles/1742-FoodPrices_web.pdf (accessed 5.13.2015).

Acemoglu, D., Ozdaglar, A., 2011. Opinion Dynamics and Learning in Social Networks. *Dynamic Games and Applications* 1(1): 3–49.

Acharya, S., Chand, P., Birthal, S., Negi, D., 2012. Market Integration and Price Transmission in India: A Case of Rice and Wheat with Special Reference to the World Food Crisis of 2007/08. Food and Agriculture Organization. Rome. http://www.fao.org/3/a-an034e.pdf (accessed 2.28.2014).

Afifi, A., Elashoff, R., 1966. Missing Observations in Multivariate Statistics: I. Review of the Literature. *Journal of the American Statistical Association* 61(315): 595–604.

Ahluwalia, M.S., 2002. Economic Reforms in India Since 1991: Has Gradualism Worked? *Journal of Economic Perspectives* 16(3): 67–88.

Alesina, A., Gatti, R., 1995. Independent Central Banks: Low Inflation at No Cost? *The American Economic Review* 85(2): 196–200.

Alexandratos, N., Bruinsma, J., 2012. World Agriculture towards 2030/2050: The 2012 Revision. *ESA Working Paper* 03(12).

AMIS, 2015. Market Monitor (Published Regularly). http://www.amis-outlook.org/amis-monitoring/monthly-report/en/ (accessed 10.8.2015).

AMIS, 2013. AMIS Progress and Acitivities since October 2012. Third meeting of the gobal food market information group, 23-24 April 2013, Paris, OECD Headquarters. http://www.amis-outlook.org/fileadmin/user_upload/amis/docs/market_group_3/IG_13_0_Progress_Report.pdf (accessed 2.7.2014).

AMIS, 2012a. Methodology: Towards Best Practices. Supply & Demand Balances for AMIS Commodities. Second meeting of the Global Food Market Information Group, 2-4 October 2012, Rome, FAO Headquarters. http://www.amis-outlook.org/fileadmin/user_upload/amis/docs/market_group_2/Presentations_3_Oct/4_Methodology.pdf (accessed 12.9.2013).

AMIS, 2012b. Global Strategy to Improve Agricultural and Rural Statistics. First meeting of the global food market information group, Rome, 9-10 February 2012. http://www.amis-outlook.org/fileadmin/user_upload/amis/docs/market_group_1/Secretariat-Global_Strategy.pdf (accessed 12.9.2013).

AMIS, 2011a. Agricultural Market Information System (AMIS): Terms of Reference. http://www.amis-outlook.org/fileadmin/user_upload/amis/docs/Inception_meeting/AMIS_TERMS_OF_REFERENCE.pdf (accessed 12.9.2013).

AMIS, 2011b. Enhancing Market Transparency. Interim Report. http://documents.wfp.org/stellent/groups/public/documents/newsroom/wfp242345.pdf (accessed 12.9.2013).

Anderson, K., Croser, J., Sandri, D., 2010. Agricultural Distortion Patterns since the 1950s : What Needs Explaining? *Centre for International Economic Studies, Discussion Paper* 1013.

Anderson, K., Ivanic, M., Martin, W., 2013. Food Price Spikes, Price Insulation and Poverty. *The Economics of Food Price Volatility* (919): 45.

Anderson, K., Martin, W., 2005. Agricultural Trade Reform and the Doha Development Agenda. *The World Economy* 28(September): 1301–1327.

Anderson, T.W., 2005. Origins of the Limited Information Maximum Likelihood and Two-Stage Least Squares Estimators. *Journal of Econometrics* 127: 1–16.

Anderson, T.W., Rubin, H., 1950. The Asymptotic Properties of Estimates of the Parameters of a Single Equation in a Complete System of Stochastic Equations. *The Annals of Mathematical Statistics* 21(4): 570–582.

Antoniou, A., Ergul, N., Holmes, P., 1997. Market Efficiency, Thin Trading and Non-Linear Behavior: Evidence from an Emerging Market. *European Financial Management* 3(2): 175–190.

Arellano, M., Bond, S., 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies* 58(2): 277–297.

Arellano, M., Bover, O., 1995. Another Look at the Instrumental Variable Estimation of Error-Components Models. *Journal of Econometrics* 68(1): 29–51.

Arezki, R., Brückner, M., 2011. Food Prices and Political Instability. *IMF Working Papers* 11(62).

Bailey, D., Brorsen, B., 1998. Trends in the Accuracy of USDA Production Forecasts for Beef and Pork. *Journal of Agricultural & Resource Economics* 23(2): 515–525.

Banerjee, A. V, Duflo, E., 2007. The Economic Lives of the Poor. *The Journal of Economic Perspectives* 21(1): 141–168.

Basak, S., Pavlova, A., 2013. A Model of Financialization of Commodities. *SSRN Electronic Journal* 1–57.

Basu, K., 2011. India's Foodgrain Policy: An Economic Theory Perspective. *Economic and Political Weekly* xlvi(5): 37–46.

Baum, C.F., 2006. An Introduction to Modern Econometrics Using Stata. Stata press, College Station, Texas.

Baum, C.F., Schaffer, M., Stillman, S., 2007. Enhanced Routines for Instrumental variables/GMM Estimation and Testing. *Stata Journal* (667): 1–38.

Baur, R., Orazem, P., 1994. The Rationality and Price Effects of US Department of Agriculture Forecasts of Oranges. *The Journal of Finance* 49(2): 681–695.

Baylis, K., Jolejole-Foreman, M.C., Mallory, M.L., 2013. Impact of Wheat and Rice Export Ban on Indian Market Integration, In: Selected Paper Prepared for Presentation at the Agricultural & Applied Economics Association’s 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6, 2013 Annual Meeting, August 4-6, 2013, Washington, D.C.

Bellemare, M.F., 2015. Rising Food Prices, Food Price Volatility, and Social Unrest. *American Journal of Agricultural Economics* 97(1): 1–21.

Bellman, R., 1957. Dynamic Programming. Princeton University Press, Princeton, N.J.

Benirschka, M., Binkley, J.K., 1995. Optimal Storage and Marketing over Space and Time. *American Journal of Agricultural Economics* 77(3): 512–524.

Bigman, D., Reutlinger, S., 1979. Food Price and Supply Stabilization: National Buffer Stocks and Trade Policies. *American Journal of Agricultural Economics* 61(4): 657–667.

Binswanger, H.P., Rosenzweig, M.R., 1986. Behavioural and Material Determinants of Production Relations in Agriculture. *The Journal of Development Studies* 2(3): 503–539.

Blundell, R., Bond, B., 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics* 87(1): 115–143.

Bond, S., 2002. Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice. *Portuguese Economic Journal* 1(2): 141–162.

Bouet, A., Laborde, D., 2010. Assessing the Potential Cost of a Failed Doha Round. *World Trade Review* 9(02): 319–351.

Bouët, A., Laborde, D., 2010. Why Is the Doha Development Agenda Failing ? And What Can Be Done ? *The World Economy* (00877): 1486–1516.

Bouët, A., Laborde Debucquet, D., 2012. Food Crisis and Export Taxation: The Cost of Non-Cooperative Trade Policies. *Review of World Economics* 148(1): 209–233.

Box, G.E.P., Wilson, K.B., 1951. Journal of the Royal Statistical Society. *Journal of the Royal Statistical Society* 13(1): 1–45.

Braulke, M., 1982. A Note on the Nerlove Model of Agricultural Supply Response. *International Economic Review* 23(1): 241–244.

Brennan, D., Williams, J., Wright, B.D., 1997. Convenience Yield without the Convenience: A Spatial-Temporal Interpretation of Storage. *The Economic Journal* 107(443): 1009–1022.

Brennen, M.J., 1958. The Supply of Storage. *The American Economic Review* 48(1): 50–72.

Briones, R.M., 2011. Regional Cooperation for Food Security: The Case of Emergency Rice Reserves in the ASEAN Plus Three. *Asian Development Bank Working Paper* 18.

Brockhaus, J., Kalkuhl, M., 2014. Can the Agricultural Market Information System (AMIS) Help to Reduce Food Price Volatility?, In: Selected Poster Prepared for Presentation at the Agricultural & Applied Economics Association’s 2014 AAEA Annual Meeting, Minneapolis, MN.

Cafiero, C., Bobenrieth H., E.S. a., Bobenrieth H., J.R. a., Wright, B.D., 2011. The Empirical Relevance of the Competitive Storage Model. *Journal of Econometrics* 162(1): 44–54.

Carraro, A., Romano, D., 2015. Modelling Acreage , Production and Yield Supply Response to Domestic Price Volatility, In: 4th AIEAA Conference – Innovation, Productivity and Growth.

Carter, C.A., Giha, C.R.L., 2007. The Working Curve and Commodity Storage under Backwardation. *American Journal of Agricultural Economics* 89(4): 864–872.

Chen, Y., Zhou, L.-A., 2007. The Long-Term Health and Economic Consequences of the 1959-1961 Famine in China. *Journal of Health Economics* 26(4): 659–81.

Collins, K., 2008. The Role of Biofuels and Other Factors in Increasing Farm and Food Prices. A Review of Recent Developments with a Focus on Feed Grain Markets and Market Prospects. Report commis- sioned by Kraft Food Global. June 19, 2008. http://www.globalbioenergy.org/uploads/media/0806_Keith_Collins_-_The_Role_of_Biofuels_and_Other_Factors.pdf (accessed 10.23.2013).

Colman, D., 1983. A Review of the Arts of Supply Response Analysis. *Review of Marketing and Agricultural Economics* 51(3): 201–230.

Coyle, W., 2007. The Future of Biofuels: A Global Perspective. *Amber Waves* 5(5): 24–29.

Cummings, R., Rashid, S., Gulati, A., 2006. Grain Price Stabilization Experiences in Asia: What Have We Learned? *Food Policy* 31(4): 302–312.

Daniel, C.R., Cross, A.J., Koebnick, C., Sinha, R., 2011. Trends in Meat Consumption in the United States. *Public Health Nutrition* 14(4): 575–583.

Das, S., 2015. Full NFSA Roll-out Not in This Fiscal. *The Financial Express* July 8, 2015 http://www.financialexpress.com/article/markets/full-nfsa-roll-out-not-in-this-fiscal/96853/.

Dash, D.K., 2015. “Levy Rice” System to Go from October. *The Times of India* March 2, 2015 http://timesofindia.indiatimes.com/india/Levy-rice-system-to-go-from-October/articleshow/46425615.cms.

Dawe, D., Timmer, P.C., 2012. Why Stable Food Prices Are a Good Thing: Lessons from Stabilizing Rice Prices in Asia. *Global Food Security* 1(2): 127–133.

de Brauw, A., Huang, J., Rozelle, S., 2004. The Sequencing of Reform Policies in China’s Agricultural Transition. *Economics of Transition* 12(3): 427–465.

de Janvry, A., Finan, F., Sadoulet, E., Vakis, R., 2006. Can Conditional Cash Transfer Programs Serve as Safety Nets in Keeping Children at School and from Working When Exposed to Shocks? *Journal of Development Economics* 79(2): 349–373.

Deaton, A., Laroque, G., 1996. Competitive Storage and Commodity Price Dynamics. *Journal of Political Economy* 104(5): 896–923.

Deaton, A., Laroque, G., 1995. Estimating a Nonlinear Rational Expectations Commodity Price Model with Unobservable State Variables. *Journal of Applied Econometrics* 10: 9–40.

Deaton, A., Laroque, G., 1992. On the Behaviour of Commodity Prices. *The Review of Economic Studies* 59(1): 1–23.

Demeke, M., Pangrazio, G., Maetz, M., 2009. Country Responses to the Food Security Crisis: Nature and Preliminary Implications of the Policies Pursued. FAO. http://www.fao.org/fileadmin/user_upload/ISFP/pdf_for_site_Country_Response_to_the_Food_Security.pdf (accessed 5.5.2014).

Dorosh, P. a, Rashid, S., 2012. Bangladesh Rice Trade and Price Stabilization. Implications of the 2007 / 08 Experience for Public Stocks. *IFPRI Discussion Paper* 01209(September).

Drèze, J., Khera, R., 2015. Understanding Leakages in the Public Distribution System. *Economis & Political Weekly* L(7): 39–42.

Ecker, O., Qaim, M., 2011. Analyzing Nutritional Impacts of Policies: An Empirical Study for Malawi. *World Development* 39(3): 412–428.

ECOWAS Commission, 2012. RESOGEST - Regional Food Security Reserve. http://www.inter-reseaux.org/IMG/pdf/Faisabilite_Reserve_Regionale_EN.pdf (accessed 2.12.2015).

"Edward" Yu, T.-H., Tokgoz, S., Wailes, E., Chavez, E., 2011. A Quantitative Analysis of Trade Policy Responses to Higher World Agricultural Commodity Prices. *Food Policy* 36(5): 545–561.

Efendic, A., Pugh, G., Adnett, N., 2009. Institutions and Economic Performance: System GMM Modelling of Institutional Effects in Transition. Unpublished Paper, Staffordshire University Business School, Stoke-on-Trent, UK. http://riinvestinstitute.org/pdf/Efendic_et_al.pdf (accessed 6.10.2015).

Egelkraut, T.M., Garcia, P., Irwin, S.H., Good, D.L., 2002. An Evaluation of Crop Forecast Accuracy for Corn and Soybeans: USDA and Private Information Services, In: NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, Missouri, April 22-23, 2002.

Engle, R.F., Granger, C.W.J., 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica* 55(2): 251–276.

Fama, E.F., 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance* 25(2): 383–417.

FAO, 2015. Wheat Crop Information [WWW Document]. http://www.fao.org/nr/water/cropinfo_wheat.html (accessed 5.6.2015).

FAO, 1996. Rome Declaration on World Food Security. World Food Security Summit 1996 in Rome. http://www.fao.org/docrep/003/w3613e/w3613e00.HTM (accessed 1.15.2016).

FAO, IFAD, IMF, OECD, UNCTAD, WFP, World Bank, WTO, IFPRI, UN HLTF, 2011. Price Volatility in Food and Agricultural Markets: Policy Responses. Policy Report. http://www.amis-outlook.org/fileadmin/templates/AMIS/documents/Interagency_Report_to_the_G20_on_Food_Price_Volatility.pdf (accessed 6.24.2013).

FAO-AMIS, 2015. Statistical Notes [WWW Document]. http://statistics.amis-outlook.org/data/index.html#STATISTICALNOTES (accessed 9.2.2015).

FEWS NET, 2015a. Malawi Food Security Outlook October 2015 to March 2016. http://www.fews.net/sites/default/files/documents/reports/Malawi_FSOU_2015_08.pdf (accessed 11.30.2015).

FEWS NET, 2015b. Zimbabwe Food Security Outlook Update August 2015. http://www.fews.net/southern-africa/zimbabwe/food-security-outlook-update/august-2015 (accessed 11.30.2015).

Fiott, D., 2011. "Resource-Full Revolutions": The European Union, Natural Resources and the Southern Neighbourhood, In: Biscop, S., Balfour, R., Emerson, M. (Eds.), An Arab Springboard for EU Foreign Policy? Academia Press, Gent, pp. 49–56.

Fisher, B.S., Tanner, C., 1978. The Formulation of Price Expectations : An Empirical Test of Theoretical Models. *American Journal of Agricultural Economics* 60(2): 245–248.

Flores-Lagunes, A., 2007. Finite Sample Evidence of IV Estimators under Weak Instruments. *Journal of Applied Econometrics* 22(3): 677–694.

Foster, A.D., 1995. Prices, Credit Markets and Child Growth in Low-Income Rural Areas. *The Economic Journal* 105(430): 551–570.

Franken, J., Garcia, P., Irwin, S., 2009. Is Storage at a Loss Merely an Illusion of Spatial Aggregation? *Journal of Agribusiness* 2: 65–84.

G20, 2011a. Ministerial Declaration: Action Plan on Food Price Volatility and Agriculture. Meeting of G20 Agriculture Ministers. Paris, 22 and 23 June 2011. http://agriculture.gouv.fr/IMG/pdf/2011-06-23_-_Action_Plan_-_VFinale.pdf (accessed 8.15.2013).

G20, 2011b. Cannes Summit Final Declaration - "Building Our Common Future: Renewed Collective Action for the Benefit of All." Cannes, 2011. http://www.amis-outlook.org/fileadmin/user_upload/amis/docs/Inception_meeting/Cannes_Summit_final_declaration.pdf (accessed 9.18.2013).

Gabre-Madhin, E.Z., 2001. Market Institutions, Transaction Costs, and Social Capital in the Ethiopian Grain Market. IFPRI Research Report. http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/49194

Galtier, F., 2014. Which Role for Storage Policies in Managing Grain Price Instability ? Some Insights from a Thought Experiment. Unpublished manuscript. http://www.fao.org/fileadmin/templates/est/meetings/stocks/Galtier_Article_on_storage_policies.pdf (accessed 1.19.2015).

Galtier, F., 2013. Managing Food Price Instability: Critical Assessment of the Dominant Doctrine. *Global Food Security* 2(2): 72–81.

Galton, F., 1907. Vox Populi - The Wisdom of Crowds. *Nature* 75: 450–451.

Ganesh-Kumar, A., Mehta, R., Pullabhotla, H., Prasad, S., Ganguly, K., Gulati, A., 2012. Demand and Supply of Cereals in India 2010-2025. IFPRI Discussion Paper. New Delhi.

Garcia, P., Irwin, S., Leuthold, R., Yang, L., 1997. The Value of Public Information in Commodity Futures Markets. *Journal of Economic Behavior & Organization* 32(4): 559–570.

Gerber, N., Eckert, M. van, Breuer, T., 2008. The Impacts of Biofuel Production on Food Prices. *ZEF Discussion Papers* 127(December).

Getnet, K., Verbeke, W., Viaene, J., 2005. Feasibility of on-Farm Commercial Grain Storage in the Smallholder Agriculture of Ethiopia. *Outlook on Agriculture* 34(1): 41–47.

Ghatak, S., Seale, J., 2001. Supply Response and Risk in Chinese Agriculture. *Journal of Development Studies* 37(5): 141–150.

Gilbert, C.L., 2011a. International Agreements for Commodity Price Stabilisation. *OECD Food, Agriculture and Fisheries Working Papers* (53).

Gilbert, C.L., 2011b. Food Reserves in Developing Countries: Trade Policy Options for Improved Food Security. *ICTSD Programme on Agricultural Trade and Sustainable Development, Issue Paper* 37.

Glauber, J.W., Helmberger, P.G., Miranda, M.J., 1989. Four Approaches to Commodity Market Stabilization: A Comparative Analysis. *American Journal of Agricultural Economics* 71(2): 326–337.

Good, D.L., Irwin, S.H., 2006. Understanding USDA Corn and Soybean Production Forecasts : Methods , Performance and Market Impacts over 1970-2005. AgMAS Project Research Report 2006-01.

Gorissen, D., Couckuyt, I., Demeester, P., Dhaene, T., Crombecq, K., 2010. A Surrogate Modeling and Adaptive Sampling Toolbox for Computer Based Design. *Journal of Machine Learning Research* 11: 2051–2055.

Gouel, C., 2014a. Food Price Volatility and Domestic Stabilization Policies in Developing Countries, In: Chavas, J.-P., Hummels, D., Wright, B.D. (Eds.), The Economics of Food Price Volatility. University of Chicago Press, pp. 261–306.

Gouel, C., 2014b. Trade Policy Coordination and Food Price Volatility. *CEPII Working Paper* 23(December).

Gouel, C., 2013a. RECS: MATLAB Solver for Rational Expectations Models with Complementarity Equations - Version 0.6. (No. 0.6). http://www.recs-solver.org (accessed 8.20.2014).

Gouel, C., 2013b. Rules versus Discretion in Food Storage Policies. *American Journal of Agricultural Economics* 95(4): 1029–1044.

Gouel, C., 2013c. Optimal Food Price Stabilisation Policy. *European Economic Review* 57: 118–134.

Gouel, C., 2011. Agricultural Price Instability and Optimal Stabilisation Policies. *PhD Thesis*. Département d'Économie, École Polytechnique.

Gouel, C., Gautam, M., Martin, W., 2014. Managing Food Price Volatility in a Large Open Country: The Case of Wheat in India. Forthcoming. http://www.worldbank.org/content/dam/Worldbank/Event/DEC/DECAR-food-conference-sep-2014/DECAR-Food-Conference-Sep18-19-PAPER-Gautam-India-Managing Wheat Price Volatility 2014_06_07.pdf (accessed 10.28.2014).

Gouel, C., Jean, S., 2015. Optimal Food Price Stabilization in a Small Open Developing Country. *World Bank Economic Review* 29(1): 72–101.

Government of Ethiopia, 2015. Humanitarian Requirements. Mid-Year Review 2015. Joint Government and Humanitarian Partners' Document. www.dppc.gov.et/downloadable/reports/appeal/2015/HRD-Revised August 2015.pdf (accessed 12.3.2015).

Gulati, A., Jain, S., 2013. Buffer Stocking Policy in the Wake of NFSB : Concepts, Empirics, and Policy Implications. *Commission for Agricultural Costs and Prices, Department of Agriculture & Cooperation. Discussion Paper* 6.

Gulati, A., Jain, S., Hoda, A., 2013. Farm Trade : Tapping the Hidden Potential. *Commission for Agricultural Costs and Prices, Department of Agriculture & Cooperation. Ministry of Agriculture. Government of India. Discussion Paper* 3.

Gulati, A., Saini, S., 2015. Leakages from Public Distribution System (PDS) and the Way Forward. *ICRIER Working Paper* 294(January).

Gulati, A., Saini, S., 2014. The National Food Security Act: Challenges and Options, Indian Economy since Independence. Academic Foundation, New Delhi.

Gupta, N., 2013. Government Intervention in Grain Markets in India : Rethinking the Procurement Policy. *Centre for Development Economics Working Paper* 231.

Gustafson, R.L., 1958. Carryover Levels for Grains A Method for Determining Amounts That Are Optimal under Specified Conditions. *United States Department of Agriculture, Technical Bulletin* 1178.

Gustavsson, J., Cederberg, C., Sonesson, U., van Otterdijk, R., Meybeck, A., 2011. Global Food Losses and Food Waste, In: FAO & SIK, Study Conducted for the International Congress SAVE FOOD! At Interpack 2011, Düsseldorf, Germany.

Haberl, H., Erb, K.-H., Krausmann, F., Bondeau, A., Lauk, C., Müller, C., Plutzar, C., Steinberger, J.K., 2011. Global Bioenergy Potentials from Agricultural Land in 2050: Sensitivity to Climate Change, Diets and Yields. *Biomass & Bioenergy* 35(12): 4753–4769.

Haile, M.G., 2015. Volatility of International Food Prices. Impacts on Resource Allocation and on Food Supply Response. *Doctoral Thesis*. Zentrum für Entwicklungsforschung, University of Bonn.

Haile, M.G., Brockhaus, J., Kalkuhl, M., 2016a. Short-Term Acreage Forecasting and Supply Elasticities for Staple Food Commodities in Major Producer Countries. *Forthcoming*.

Haile, M.G., Kalkuhl, M., von Braun, J., 2016b. Worldwide Acreage and Yield Response to International Price Change and Volatility: A Dynamic Panel Data Analysis for Wheat, Rice, Corn, and Soybeans. *American Journal of Agricultural Economics* 98(1): 172–190.

Haile, M.G., Kalkuhl, M., von Braun, J., 2014. Inter- and Intra-Seasonal Crop Acreage Response to International Food Prices and Implications of Volatility. *Agricultural Economics* 45: 693–710.

Haile, M.G., Kalkuhl, M., von Braun, J., 2013. Short-Term Global Crop Acreage Response to International Food Prices and Implications of Volatility. *ZEF-Discussion Papers on Development Policy* 175(February).

Hansen, L., 1982. Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica* 50(4): 1029–1054.

Hansen, L.P., Heaton, J., Yaron, A., 1996. Finite-Sample Properties of Some Alternative GMM Estimators. *Journal of Business & Economic Statistics* 14(3): 262–280.

Hausman, J.A., 1983. Specification and Estimation of Simultaneous Equation Models, In: Engle, R.F., McFadden, D. (Eds.), Handbook of Econometrics. Elsevier, pp. 391–448.

Headey, D., 2014. Food Prices and Poverty Reduction in the Long Run. *IFPRI Discussion Paper* 01331(March).

Headey, D., 2010. Rethinking the Global Food Crisis, The Role of Trade Shocks. *IFPRI Discussion Paper* 00958(March).

Headey, D., Fan, S., 2008. Anatomy of a Crisis: The Causes and Consequences of Surging Food Prices. *Agricultural Economics* 39(Supplement): 375–391.

Heckelei, T., 2002. Calibration and Estimation of Programming Models for Agricultural Supply Analysis. *Habilitationsschrift*. Landwirtschaftliche Fakultät, University of Bonn.

Heckelei, T., Swinnen, J., 2012. Introduction to the Special Issue of the World Trade Review on “standards and Non-Tariff Barriers in Trade.” *World Trade Review* 11(03): 353–355.

Helmberger, P.G., Weaver, R., 1977. Welfare Implications of Commodity Storage under Uncertainty. *American Journal of Agricultural Economics* 59: 639–651.

Hendry, D.F., 1984. Monte Carlo Experimentation in Econometrics, In: Griliches, Z., Intriligator, M.D. (Eds.), Handbook of Econometrics. Elsevier, pp. 937–976.

High Level Committe on Restructuring of the FCI, 2015. Report of the High Level Committe on Reorienting the Role and Restructuring of Food Corporation of India. http://fci.gov.in/app/webroot/upload/News/Report of the High Level Committee on Reorienting the Role and Restructuring of FCI_English.pdf (accessed 2.2.2016).

HLPE, 2011. Price Volatility and Food Security. Committee on World Food Security. High Level Panel of Experts Report 1. Rome. http://www.fao.org/fileadmin/user_upload/hlpe/hlpe_documents/HLPE-price-volatility-and-food-security-report-July-2011.pdf (accessed 2.3.2014).

Hoda, A., Gulati, A., 2013. India's Agricultural Trade Policy and Sustainable Development. *ICTSD Issue Paper* (49).

Holt, M.T., McKenzie, A.M., 2003. Quasi-Rational and Ex Ante Price Expectations in Commodity Supply Models: An Empirical Analysis of the US Broiler Market. *Journal of Applied Econometrics* 18(4): 407–426.

Holtz-Eakin, D., Newey, W., Rosen, H.S., 1988. Estimating Vector Autoregressions with Panel Data. *Econometrica* 56(6): 1371–1395.

Huang, J., Rozelle, S., 2006. The Emergence of Agricultural Commodity Markets in China. *China Economic Review* 17(3): 266–280.

Huang, J., Rozelle, S., 1996. Technological Change: Rediscovering the Engine of Productivity Growth in China's Rural Economy. *Journal of Development Economics* 49: 337–369.

Huang, J., Wang, X., Rozelle, S., 2013. The Subsidization of Farming Households in China's Agriculture. *Food Policy* 41: 124–132.

Huang, J., Wang, X., Zhi, H., Huang, Z., Rozelle, S., 2011. Subsidies and Distortions in China's Agriculture: Evidence from Producer-Level Data. *Australian Journal of Agricultural and Resource Economics* 55(1): 53–71.

Innes, R., 1990. Uncertainty, Incomplete Markets and Government Farm Programs. *Southern Economic Journal* 57(1): 47–65.

IPCC, 2007. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, IPCC, In: Parry, M., Canziani, O., Palutikof, J., van der Linden, P., Hanson, C. (Eds.), Climate Change 2007: Impacts, Adaptation and Vulnerability. p. 996.

Isengildina, O., 2004. Evaluation of USDA Interval Forecasts of Corn and Soybean Prices. *American Journal of Agricultural Economics* 86(4): 990–1004.

Isengildina, O., Irwin, S.H., Good, D.L., 2006. Are Revisions to USDA Crop Production Forecasts Smoothed? *American Journal of Agricultural Economics* 88(November): 1091–1104.

Isengildina, O., Irwin, S.H., Good, D.L., 2004. Does the Market Anticipate Smoothing in USDA Crop Production Forecasts ?, In: Selected Paper Presented at the American Agricultural Economics Association Annual Meetings Denver, CO, August.

Islam, N., Thomas, S., 1996. Foodgrain Price Stabilization in Developing Countries. IFPRI Food Policy Review.

Ivanic, M., Martin, W., 2008. Implications of Higher Global Food Prices for Poverty in Low-Income Countries. *Agricultural Economics* 39(Supplement): 405–416.

Jean, S., Laborde, D., Martin, W., 2010. Formulas and Flexibility in Trade Negotiations: Sensitive Agricultural Products in the World Trade Organization's Doha Agenda. *World Bank Economic Review* 24(3): 500–519.

Jha, S., Srinivasan, P. V, Landes, M., 2007. Indian Wheat and Rice Sector Policies and the Implications of Reform. *USDA Economic Research Report* 41.

Jones, R.H., 1980. Maximum Likelihood Fitting of ARMA Models to Time Series With Missing Observations. *Technometrics* 22(3): 389–395.

Just, R.E., Wenninger, Q., 1999. Are Crop Yields Normally Distributed? *American Journal of Agricultural Economics* 81(2): 287–304.

Kalkuhl, M., 2014. How Strong Do Global Commodity Prices Influence Domestic Food Prices in Developing Countries ? A Global Price Transmission and Vulnerability Mapping Analysis. *ZEF-Discussion Papers on Development Policy* 191(May).

Kalkuhl, M., Kornher, L., Kozicka, M., Boulanger, P., Torero, M., 2013. Conceptual Framework on Price Volatility and Its Impact on Food and Nutrition Security in the Short Term. *Foodsecure Working Paper* 15(September).

Khera, R., 2011. India's Public Distribution System: Utilisation and Impact. *Journal of Development Studies* 47(7): 1038–1060.

Kleibergen, F., Paap, R., 2006. Generalized Reduced Rank Tests Using the Singular Value Decomposition. *Journal of Econometrics* 133(1): 97–126.

Koester, U., 1986. Regional Cooperation To Improve Food Security in Southern and Eastern African Countries Food Policy. *IFPRI Research Report* 53.

Kornher, L., 2015. Food Price Volatility: The Role of Stocks and Trade. *Doctoral Thesis*. Zentrum für Entwicklungsforschung, University of Bonn.

Kornher, L., Kalkuhl, M., 2015. Cost and Benefits from Regional Cooperation on Grain Reserves: The Case of ECOWAS, In: International Conference of Agricultural Economists, Milan, August 8 - 14.

Kornher, L., Kalkuhl, M., 2013. Food Price Volatility in Developing Countries and Its Determinants. *Quarterly Journal of International Agriculture* 52(4): 30.

Kozicka, M., Kalkuhl, M., Brockhaus, J., 2015a. Food Grain Policies in India and Their Implications for Stocks and Fiscal Costs: A Partial Equilibrium Analysis, In: Ecomod 2015.

Kozicka, M., Kalkuhl, M., Saini, S., Brockhaus, J., 2015b. Modelling Indian Wheat and Rice Sector Policies. *ZEF Discussion Papers* 197.

Laborde, D., Martin, W., 2012. Agricultural Trade: What Matters in the Doha Round? *Annual Review of Resource Economics* 4(1): 265–283.

Landes, R., Gulati, A., 2004. Farm and Performance Sector Reform Agenda. *Economic and Political Weekly* 39(32): 3611–3619.

Larson, D., Lampietti, J., Gouel, C., Cafiero, C., Roberts, J., 2014. Food Security and Storage in the Middle East and North Africa. *The World Bank Economic Review* 28(1): 48–73.

Leaver, R., 2004. Measuring the Supply Response Function of Tobacco in Zimbabwe. *Agrekon* 43(1): 113–131.

Lence, S.H., Hayes, D.J., 2002. U.S. Farm Policy and the Volatility of Commodity Prices and Farm Revenues. *American Journal of Agricultural Economics* 84(2): 335–351.

Lin, J.Y., 1992. Rural Reforms and Agricultural Growth in China. *The American Economic Review* 82(1): 34–51.

Lin, J.Y., 1991. The Household Responsibility System Reform and the Adoption of Hybrid Rice in China *. *Journal of Development Economics* 36(2): 353–372.

Little, R.J.A., 1992. Regression with Missing X's: A Review. *Journal of the American Statistical Association* 87(420): 1227–1237.

Little, R.J.A., Rubin, D.B., 2002. Statistical Analysis of Missing Data, 2nd ed. John Wiley, New York.

Liu, B., Keyzer, M., van den Boom, B., Zikhali, P., 2012. How Connected Are Chinese Farmers to Retail Markets? New Evidence of Price Transmission. *China Economic Review* 23(1): 34–46.

Lorenz, J., Rauhut, H., Schweitzer, F., Helbing, D., 2011. How Social Influence Can Undermine the Wisdom of Crowd Effect. *PNAS* 108(22): 9020–9025.

MacKinnon, J.G., 2010. Critical Values for Co-Integration Tests. *Queen's Economics DepartmentWorking Paper* (1227).

Malthus, T., 1798. An Essay on the Principle of Population. Reprint 1998, Electronic Scholarly Publishing Project, Printed for J. Johnson, in St. Paul's Church-Yard, London, UK.

Martin, W., Anderson, K., 2011. Export Restrictions and Price Insulation During Commodity Price Booms. *American Journal of Agricultural Economics* 94(2): 422–427.

Maystadt, J.-F., Ecker, O., 2014. Extreme Weather and Civil War: Does Drought Fuel Conflict in Somalia through Livestock Price Shocks? *American Journal of Agricultural Economics* 96(4): 1157–1182.

McKenzie, A.M., 2008. Pre-Harvest Price Expectations for Corn: The Information Content of USDA Reports and New Crop Futures. *American Journal of Agricultural Economics* 90(2): 351–366.

Mekonnen, M., Hoekstra, A., 2011. The Green, Blue and Grey Water Footprint of Crops and Derived Crop Products. *Hydrology and Earth System Sciences* 15: 1577–1600.

Mekonnen, M., Hoekstra, A., 2010. The Green, Blue and Grey Water Footprint of Farm Animals and Animal Products. Value of Water Research Report Series No. 48, UNESCO-IHE, Delft, the Netherlands. http://doc.utwente.nl/76912/ (accessed 11.16.2013).

Miao, Y., Wu, W., Funke, N., 2011. Reviving the Competitive Storage Model: A Holistic Approach to Food Commodity Prices. *IMF Working Papers* 64.

Minot, N., Dewina, R., 2015. Are We Overestimating the Negative Impact of Higher Food Prices? Evidence from Ghana. *Agricultural Economics* 46: 1–15.

Miranda, M.J., Fackler, P., 2011. CompEcon Toolbox for Matlab. http://www4.ncsu.edu/~pfackler/compecon/toolbox.html (accessed 8.20.2014).

Miranda, M.J., Glauber, J., 1995. Solving Stochastic Models of Competitive Storage and Trade by Chebychev Collocation Methods. *Agricultural and Resource Economics Review* 24(1): 70–77.

Miranda, M.J., Glauber, J.W., 1993. Estimation of Dynamic Nonlinear Rational Expectations Models of Primary Commodity Markets with Private and Government Stockholding. *The Review of Economics and Statistics* 75(3): 463–470.

Miranda, M.J., Helmberger, P., 1988. The Effects of Commodity Price Stabilization Programs. *The American Economic Review* 78(1): 46–58.

Miranda, M.J., Rui, X., 1999. An Empirical Reassessment of the Commodity Storage Model. Unpublished Manuscript. http://wpage.unina.it/cafiero/storage/Mirrui99.pdf (accessed 9.29.2014).

Mooij, J., 1994. Food, Law and Politics in India. The Political Economy of the Essential Commodities Act. Unpublished Manuscript. http://citeseerx.ist.psu.edu/viewdoc/download;jsessionid=69789879809A3503D070B63182BE5D00?doi=10.1.1.199.2631&rep=rep1&type=pdf (accessed 10.5.2015).

Moschini, G., Hennessy, D.A., 2001. Uncertainty, Risk Aversion, and Risk Management for Agricultural Producers, In: Gardner, B., Rausser, G. (Eds.), Handbook of Agricultural Economics. Elsevier, pp. 87–153.

Mustard, A., Singh, S.K., 2015. India Grain and Feed Annual. USDA Report. http://gain.fas.usda.gov/Recent GAIN Publications/Grain and Feed Annual_New Delhi_India_2-14-2014.pdf (accessed 9.1.2015).

Muth, J., 1961. Rational Expectations and the Theory of Price Movements. *Econometrica* 29(3): 315–335.

Myers, R.J., 2006. On the Costs of Food Price Fluctuations in Low-Income Countries. *Food Policy* 31(4): 288–301.

Nerlove, M., 1979. The Dynamics of Supply: Restrospect and Prospect. *American Journal of Agricultural Economics* 61(1972): 874–888.

Newbery, D., Stiglitz, J., 1982. Optimal Commodity Stock-Piling Rules. *Oxford Economic Papers* 34(3): 403–427.

Newbery, D., Stiglitz, J., 1981. The Theory of Commodity Price Stabilization. Oxford University Press, Oxford.

Nickell, S., 1985. Error Correction, Partial Adjustment and All That: An Expository Note. *Oxford Bulletin of Economics and Statistics* 47(2): 119–130.

Oxfam, 2015. Entering Uncharted Waters. El Niño and the Threat to Food Security. Oxfam Media Briefing. https://www.oxfam.org/en/research/entering-uncharted-waters-el-nino-and-threat-food-security (accessed 11.30.2015).

Oxfam, 2011. Preparing for Thin Cows. Why the G20 Should Keep Buffer Stocks on the Agenda. Briefing Note. https://www.oxfam.org/sites/www.oxfam.org/files/bn-preparing-thin-cows-food-reserves-210611-en.pdf (accessed 11.30.2015).

Paquotte, P., 2015. Country Collaboration and the Forecasting Excercise, In: Eighth Session of the AMIS Global Food Market Information Group. 19 October 2015. Milan.

Parente, P.M.D.C., Santos Silva, J.M.C., 2012. A Cautionary Note on Tests of Overidentifying Restrictions. *Economics Letters* 115(2): 314–317.

Parfitt, J., Barthel, M., Macnaughton, S., 2010. Food Waste within Food Supply Chains: Quantification and Potential for Change to 2050. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences* 365(1554): 3065–81.

Paulino, L., Tseng, S., 1980. A Comparative Study of FAO and USDA Data on Production, Area, and Trade of Major Food Staples. IFPRI Research Report. http://www.ifpri.org/sites/default/files/publications/rr19.pdf (accessed 4.7.2014).

Persyn, D., Westerlund, J., 2008. Error-Correction-Based Cointegration Tests for Panel Data. *Stata Journal* 8(2): 232–241.

Peterson, H.H., Tomek, W.G., 2005. How Much of Commodity Price Behavior Can a Rational Expectations Storage Model Explain? *Agricultural Economics* 33(3): 289–303.

Pursell, G., 2014. India's Food Grain Policies and the Public Distribution System: The Case of Rice. Who Wins, Who Loses, and by How Much? *ASARC Working Paper* 04.

Ramachandran, K.S., 2005. Subsidies: A Bottomless Bucket. Northern Book Center, New Delhi.

Ramey, G., Ramey, V. a, 1995. Cross-Country Evidence on the Link Between Volatility and Growth. *American Economic Review* 85(5): 1138–1151.

Ravallion, M., 1987. Markets and Famines. Oxford University Press, Oxford.

Reardon, T., Minten, B., 2011. The Quiet Revolution in India's Food Supply Chains. *IFPRI Discussion Paper* 01115(September).

Roberts, M.J., Schlenker, W., 2009. World Supply and Demand of Food Commodity Calories. *American Journal of Agricultural Economics* 91(5): 1235–1242.

Romero-Aguilar, R.S., Miranda, M.J., 2015. Sustainability of Regional Food Reserves When Default Is Possible, In: Selected Paper Prepared for Presentation for the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, CA, July 26-28.

Romero-Aguilar, R.S., Miranda, M.J., 2014. Food Security for Whom? The Effectiveness of Food Reserves in Poor Developing Countries, In: Selected Paper Prepared for Presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis,MN, July 27-29.

Roodman, D., 2009. How to Do xtabond2: An Introduction to Difference and System GMM in Stata. *Stata Journal* 9(1): 86–136.

Rosenzweig, M.R., Stark, O., 1989. Consumption Smoothing, Migration, and Marriage: Evidence from Rural India. *The Journal of Political Economy* 97(4): 905–926.

Rosenzweig, M.R., Wolpin, K.I., 1993. Credit Market Constraints, Consumption Smoothing, and the Accumulation of Durable Production Assets in Low-Income Countries: Investments in Bullocks in India. *Journal of Political Economy* 101(2): 223–244.

Sahley, C., Groelsema, B., Marchione, T., Nelson, D., 2005. The Governance Dimensions of Food Security in Malawi. USAID. http://sarpn.org/documents/d0001649/P1998-USAID_Malawi_Sept2005.pdf (accessed 1.29.2015).

Saini, S., Kozicka, M., 2014. Evolution and Critique of Buffer Stocking Policy of India. *ICRIER Working Paper* 283(September).

Salant, S.W., 1983. The Vulnerability of Price Stabilization Schemes to Speculative Attack. *Journal of Political Economy* 91(1): 1.

Sanders, D., Manfredo, M., 2003. USDA Livestock Price Forecasts: A Comprehensive Evaluation. *Journal of Agricultural and Resource Economics* 28(2): 316–334.

Sandmo, A., 1971. On the Theory Under of Price the Competitive Uncertainty Firm. *The American Economic Review* 61(1): 65–73.

Sen, A., 1980. Famines. *World Development* 8(9): 613–621.

Sharon, M.E.M., Abirami, C.V.K., Alagusundaram, K., 2014. Grain Storage Management in India. *Journal of Postharvest Technology* 02(01): 12–24.

Shiller, R., 2003. From Efficient Markets Theory to Behavioral Finance. *Journal of Economic Perspectives* 17(1): 83–104.

Shreedhar, G., Gupta, N., Pullabhotla, H., Ganesh-Kumar, A., Mishra, A., 2012. A Review of Input and Output Policies for Cereals Production in India. *IFPRI Discussion Paper* 01159(January): 1–52.

Sidhir, B., 2004. Onion Prices and State Intervention. *Economic and Political Weekly* 39(33): 3684–3686.

Srinivasan, P.., Jha, S., 2001. Liberalized Trade and Domestic Price Stability. The Case of Rice and Wheat in India. *Journal of Development Economics* 65(2): 417–441.

Srinivasan, P.V., Jha, S., 1999. Food Stabilisation Security through Buffer Stocks vs Variable Levies. *Economic and Political Weekly* 34(46): 3299–3304.

Sumner, D. a., Mueller, R. a. E., 1989. Are Harvest Forecasts News? USDA Announcements and Futures Market Reactions. *American Journal of Agricultural Economics* 71(1): 1.

Surowiecki, J., 2004. The Wisdom of Crowds: Why the Many Are Smarter Than the Few and How Collective Wisdom Shapes Business, Economics, Societies and Nations. Doubleday, New York.

Swinnen, J.F.M., 2010. The Right Price of Food. *LICOS Discussion Paper Series* 259.

Tadesse, G., Algieri, B., Kalkuhl, M., Braun, J. von, 2014. Drivers and Triggers of International Food Price Spikes and Volatility. *Food Policy* 47: 117–128.

Tang, K., Xiong, W., 2012. Index Investment and the Financialization of Commodities. *Financial Analysts Journal* 68(6): 54–74.

Tao, F., Yokozawa, M., Xu, Y., Hayashi, Y., Zhang, Z., 2006. Climate Changes and Trends in Phenology and Yields of Field Crops in China, 1981-2000. *Agricultural and Forest Meteorology* 138(1-4): 82–92.

Thaindian News, 2008. Delhi Government Imposes Limits on Food Grain Stocking. April 14, 2008 http://www.thaindian.com/newsportal/business/delhi-government-imposes-limits-on-food-grain-stocking_10037937.html.

Tiffin, R., 2004. Shrinking the Posterior: A Note on the Nerlovian Model. *Journal of Agricultural Economics* 55(1): 115–121.

Timmer, C.P., 2010. Reflections on Food Crises Past. *Food Policy* 35(1): 1–11.

Timmer, C.P., 1996. Does Bulog Stabilise Rice Prices in Indonesia? Should It Try?, Bulletin of Indonesian Economic Studies.

Timmer, C.P., 1989. Food Price Policy. The Rationale for Government Intervention. *Food Policy* 14(1): 17–27.

Timmer, P.C., 2013. Price Stabilization, Self-Sufficiency and Food Security: Some Lessons from the Indonesian Experience, In: Galtier, F. (Ed.), Managing Food Price Instability in Developing Countries. A Critical Analysis of Strategies and Instruments. AFD, Paris, pp. 177–181.

Townsend, R.M., 1995. Consumption Insurance: An Evaluation of Risk-Bearing Systems in Low-Income Economies. *The Journal of Economic Perspectives* 9(3): 83–102.

Townsend, R.M., 1994. Risk and Insurance in Village India. *Econometrica* 62(3): 539–591.

United Nations, 2015a. 70/1. Transforming Our World: The 2030 Agenda for Sustainable Development. Resolution adopted by the General Assembly on 25 September 2015. http://www.un.org/ga/search/view_doc.asp?symbol=A/RES/70/1&Lang=E (accessed 12.9.2015).

United Nations, 2015b. World Population Prospects: The 2015 Revision. http://esa.un.org/unpd/wpp/ (accessed 12.9.2015).

USDA, 2012. Understanding USDA Crop Forecasts. http://www.amis-outlook.org/fileadmin/user_upload/amis/docs/market_group_1/USDA_crop_forecasting.pdf

von Braun, J., 2008. High Food Prices: The Proposed Policy Actions, In: Keynote Address to the ECOSOC Special Meeting "The Global Food Crisis" United Nations Headquarters, New York. May, 20.

von Braun, J., Algieri, B., Kalkuhl, M., 2014. World Food System Disruptions in the Early 2000s: Causes, Impacts and Cures. *World Food Policy* 1(1).

von Braun, J., Kalkuhl, M., 2015. International Science and Policy Interaction for Improved Food and Nutrition Security: Toward an International Panel on Food and Nutrition (IPFN). *ZEF Working Paper Series* 142.

von Braun, J., Tadesse, G., 2012. Global Food Price Volatility and Spikes : An Overview of Costs, Causes, and Solutions. *ZEF-Discussion Papers on Development Policy* 161.

von Braun, J., Torero, M., 2009. Implementing Physical and Virtual Food Reserves to Protect the Poor and Prevent Market Failure. *IFPRI Policy Brief* 10(February).

Vul, E., Pashler, H., 2008. Measuring the Crowd Within: Probabilistic Representation Within Individuals. *Psychological Science* 19(7): 645–647.

Wang, J., Mendelsohn, R., Dinar, A., Huang, J., Rozelle, S., Zhang, L., 2009. The Impact of Climate Change on China's Agriculture. *Agricultural Economics* 40(3): 323–337.

Westerlund, J., 2007. Testing for Error Correction in Panel Data. *Oxford Bulletin of Economics and Statistics* 69(6): 709–748.

WFP, 2016. Procurement [WWW Document]. https://www.wfp.org/procurement (accessed 2.2.2016).

WFP, 2014. WFP Logistics in 2014. http://documents.wfp.org/stellent/groups/public/documents/communications/wfp275144.pdf (accessed 2.2.2016).

WFP, 2013. Food Procurement Annual Report 2013. http://documents.wfp.org/stellent/groups/public/documents/communications/wfp264134.pdf (accessed 2.2.2016).

Williams, J., 1987. Futures Markets: A Consequence of Risk Aversion or Transactions Costs? *Journal of Political Economy* 95(5): 1000–1023.

Williams, J.C., Wright, B.D., 1991. Storage and Commodity Markets. Cambridge University Press, Cambridge.

Windmeijer, F., 2005. A Finite Sample Correction for the Variance of Linear Efficient Two-Step GMM Estimators. *Journal of Econometrics* 126(1): 25–51.

Working, H., 1949. The Theory of Price of Storage. *American Economic Review* 39(6): 1254–1262.

World Bank, 2011. India - Punjab Silos. Public-private partnerships success stories. Brief. Washington, DC. http://documents.worldbank.org/curated/en/2011/10/16254577/india-punjab-silos (accessed 11.18.2015).

World Bank, 2010. Food Price Increases in South Asia: National Responses and Regional Dimensions. Report. Washington, DC. http://documents.worldbank.org/curated/en/2010/06/12623641/food-price-increases-south-asia-national-responses-regional-dimensions (accessed 5.7.2015).

World Bank, 2005. Managing Food Price Risks and Instability in an Environment of Market Liberalization. Report. Washington, DC. http://siteresources.worldbank.org/INTARD/Resources/ManagingFoodPriceRisks.pdf (accessed 5.5.2014).

Wright, B., Williams, J., 1988. The Incidence of Market-Stabilising Price Support Schemes. *The Economic Journal* 98(393): 1183–1198.

Wright, B., Williams, J., 1982. The Economic Role of Commodity Storage. *The Economic Journal* 92(367): 596–614.

Yang, J., Qiu, H., Huang, J., Rozelle, S., 2008. Fighting Global Food Price Rises in the Developing World: The Response of China and Its Effect on Domestic and World Markets. *Agricultural Economics* 39: 453–464.

Yu, B., Liu, F., You, L., 2011. Dynamic Agricultural Supply Response Under Economic Transformation: A Case Study of Henan, China. *American Journal of Agricultural Economics* 94(2): 370–376.

Yu, W., Jensen, H.G., 2010. China's Agricultural Policy Transition: Impacts of Recent Reforms and Future Scenarios. *Journal of Agricultural Economics* 61(2): 343–368.

Zalewska-Mitura, A., Hall, S.G., 1999. Examining the First Stages of Market Performance : A Test for Evolving Market Efficiency. *Economic Letters* 64: 1–12.

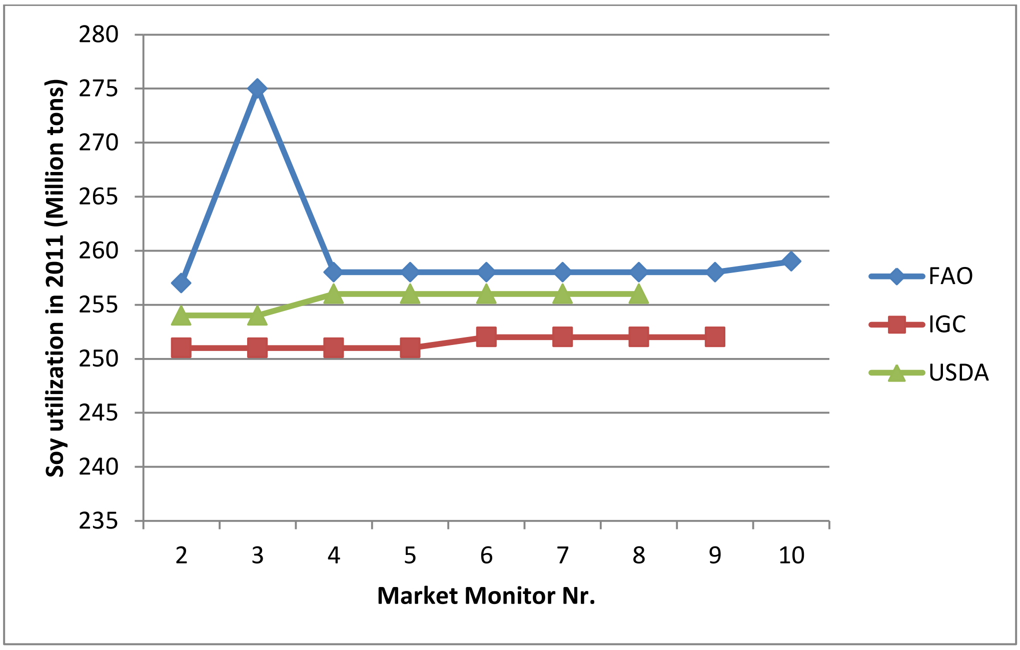
Zant, W., 1997. Stabilizing Prices in Commodity Markets: Price Bounds versus Private Stockholding. *Journal of Policy Modeling* 19(3): 253–277.

8 Appendix

8.1 Appendix for chapter 2

Some presumptive mistakes found in the data were corrected. These mistakes have been partly confirmed and afterwards corrected by AMIS. They were outliers or the marketing year was specified incorrectly. The judgements for detecting outliers were made as described in section 2.3. Only for the first mistake a figure of the uncorrected data is included but all figures are available upon request. The data was corrected as follows:

1. FAO, Soy, Utilization, 2011 estimate, Market Monitor 3: set to 257 instead of 275 (outlier). The uncorrected data looks as follows:



Note: Own illustration.

2. IGC, Rice & Soy, 2012 estimates, Market Monitor 9: Year set to 2011 instead of 2012 (data matches this year but not 2012 data)
3. IGC, Rice & Soy, 2013 forecasts, Market Monitor 9: Year set to 2012 instead of 2013 (data matches this year but not 2013 data)
4. IGC, Rice, Utilization, 2012 estimate, Market Monitor 10, Set to 468 instead of 458 (outlier)
5. IGC, Rice, Trade, 2012 estimate, Market Monitor 10, Set to 37 instead of 39 (outlier)
6. FAO, Wheat, Supply, 2012 estimate, Market Monitor 17: Set to 841 instead of 818 (outlier)
7. USDA, Maize, Production, 2013 estimate, Market Monitor 23: Set to 989 instead of 999 (outlier)

8. USDA, Maize, Supply, 2013 estimate, Market Monitor 23: Set to 1126 instead of 1136 (outlier)
9. IGC, Soy, Supply, 2013 estimate, Market Monitor 24: Set to 313 instead of 332 (outlier)
10. FAO, Wheat, Supply, 2013 estimate, Market Monitor 27: Set to 875 instead of 896 (outlier)
11. FAO, Wheat, Utilization, 2013 estimate, Market Monitor 27: Set to 685 instead of 692 (outlier)
12. FAO, Wheat, Ending stocks, 2013 estimate, Market Monitor 27: Set to 179 instead of 193 (outlier)
13. FAO, Maize, Utilization, 2013 estimate, Market Monitor 27: Set to 946 instead of 956 (outlier)
14. FAO, Maize, Ending stocks, 2013 estimate, Market Monitor 27: Set to 176 instead of 188 (outlier)

Table 8.1: Own global grain supply and demand estimates (mean of FAO, USDA, IGC)

	Report-	**Corn**				**Rice**				**Soy**				**Wheat**			
	Nr.	**2011**	**2012**	**2013**	**2014**	**2011**	**2012**	**2013**	**2014**	**2011**	**2012**	**2013**	**2014**	**2011**	**2012**	**2013**	**2014**
Ending Stocks	2	137	123			122	123			34	33			196	175		
	3	133	119			122	125			35	38			194	171		
	4	133	119			123	125			35	39			193	170		
	5	134	120			124	125			35	39			189	170		
	6	133	120			124	126			35	38			191	172		
	7	133	122			124	128			35	39			192	174		
	8	133	124			125	128			34	38			193	175		
	9		127	159			129	145		24	38				174	180	
	10		126	159			129	133			38	54			174	177	
	11		126	159			129	132			38	45			168	173	
	12		125	157			129	133			38	43			168	173	
	13		126	160			129	132			38	44			168	175	
	14		133	167			130	131			38	44			170	177	
	15		131	164			130	131			39	45			169	183	
	16		131	162			131	131			38	44			169	184	
	17		131	163			132	134			37	43			169	184	
	18			162	163		110	134			37	42				185	184
	19			165	174			134	146			42				185	185
	20			170	188			134	147		37	42				184	188
	21			174	196			133	130			42	57			183	193
	22			175	197			133	129			42	57			183	194
	23			175	198			133	128			42	57			182	193
	24			175	200			132	126			42	57			183	193
	25			174	197			132	126			42	58			183	195
	26			175	198			132	125			42	59			184	198
	27			174	198			132	125			43	60			184	200

	28				203			108	125			43	62				199
	29				206				126				61				200
Production	2	879	845			470	471			238	258			697	655		
	3	879	842			470	472			239	266			696	656		
	4	880	841			470	472			239	269			697	655		
	5	882	856			471	472			239	271			697	657		
	6	882	858			471	474			239	269			698	657		
	7	882	859			472	475			239	267			698	657		
	8	881	859			472	474			239	267			698	657		
	9		862	958			477	489		240	267				657	695	
	10		861	964			477	485			267	285			657	694	
	11		865	962			476	483			268	282			656	702	
	12		866	962			476	482			268	281			656	702	
	13		866	966			476	482			268	282			657	704	
	14		867	971			476	479			269	285			657	705	
	15		866	975			476	478			269	288			657	711	
	16		866	977			477	480			269	285			657	712	
	17		866	979			477	482			268	283			657	713	
	18			982	959		471	483			269	282				712	700
	19			985	974			483	492		270	284				713	698
	20			987	982			484	493		269	283				714	703
	21			993	990			483	485			282	307			715	717
	22			994	993			483	483			282	310			715	719
	23			994	995			484	482			284	309			715	721
	24			995	997			483	482			284	310			715	721
	25			996	1000			483	482			284	313			714	721
	26			997	1002			483	482			284	315			715	724
	27			998	1002			483	481			284	314			715	724
	28				1004			477	481			284	316				725
	29				1006				482				318				725
Supply	2	1006	981			583	593			285	292			891	856		
	3	1006	975			584	595			286	300			892	851		
	4	1007	978			584	595			287	303			889	848		
	5	1009	989			585	596			286	306			888	847		
	6	1009	990			586	597			286	304			888	848		
	7	1009	992			587	599			286	302			889	849		
	8	1009	992			587	599			286	302			891	850		
	9		995	1085			601	629		276	302				850	869	
	10		995	1087			601	614			301	329			850	868	
	11		998	1088			600	612			302	320			848	871	
	12		999	1087			601	612			302	318			848	870	
	13		999	1092			600	611			303	320			848	873	
	14		1000	1104			600	610			304	323			848	875	
	15		999	1106			600	608			304	326			847	880	
	16		999	1108			601	610			303	322			848	881	
	17		999	1109			603	613			304	319			848	882	

	18			1113	1123		579	614			304	320				881	884
	19			1119	1139			615	638		295	321				881	883
	20			1120	1151			616	639		303	321				882	887
	21			1126	1164			615	619			320	342			882	899
	22			1127	1168			615	617			320	352			883	902
	23			1127	1170			615	616			322	352			882	903
	24			1128	1172			615	614			322	352			883	903
	25			1129	1174			615	614			322	356			882	904
	26			1130	1177			616	614			322	357			883	908
	27			1136	1180			616	614			321	356			883	913
	28				1182			588	613			321	359				913
	29				1186				615				360				915
Trade	2	98	92			35	36			92	94			148	134		
	3	102	92			37	37			91	97			150	133		
	4	103	93			38	37			92	99			149	134		
	5	104	93			38	37			92	99			150	136		
	6	105	94			38	37			92	99			150	136		
	7	105	94			38	37			93	98			150	138		
	8	105	93			39	37			93	97			150	138		
	9		94	102			38	38		94	97				139	139	
	10		94	102			38	37			96	106			139	139	
	11		97	102			37	38			97	105			139	145	
	12		97	102			38	38			98	106			139	146	
	13		97	103			38	38			98	107			139	146	
	14		96	107			38	38			99	108			140	146	
	15		97	108			38	39			99	109			139	150	
	16		97	110			38	39			99	110			139	150	
	17		97	112			38	40			99	108			139	153	
	18			115	111		39	40			99	110				154	147
	19			118	114			40	40		98	111				155	149
	20			120	114			40	40		100	111				157	148
	21			124	114			40	40			112	115			160	150
	22			124	115			40	41			113	116			159	151
	23			124	114			40	41			113	116			159	152
	24			125	113			41	41			113	116			159	152
	25			125	114			42	42			113	117			159	154
	26			125	115			42	42			113	118			159	154
	27			125	116			42	42			113	117			159	155
	28				117			43	41			113	118				156
	29				119				42				118				157
Utilization	2	870	858			461	469			254	258			692	682		
	3	874	857			461	470			254	261			695	681		
	4	876	856			461	470			255	262			694	680		
	5	877	871			461	471			255	265			696	679		
	6	878	872			462	471			255	264			696	678		
	7	878	871			463	472			255	263			695	678		

8	877	869			462	472			255	263			695	677		
9		869	926			473	484		255	263				678	690	
10		871	927			472	480			263	274			678	690	
11		874	927			472	479			264	274			679	695	
12		876	927			471	479			264	274			680	696	
13		874	929			471	479			265	275			680	697	
14		868	932			470	478			265	278			679	697	
15		869	938			470	478			264	279			679	696	
16		869	942			471	479			263	277			679	695	
17		869	942			471	479			265	276			680	695	
18			945	960		468	480			264	276				694	700
19			946	963			480	492		267	277				694	698
20			944	962			481	492		264	277				693	698
21			945	965			481	489			275	292			695	705
22			945	967			482	488			276	294			696	707
23			946	967			482	488			278	292			697	709
24			947	969			483	488			279	293			696	710
25			948	972			483	488			278	295			695	708
26			948	975			483	489			279	297			695	709
27			949	979			484	489			278	296			695	711
28				976			480	489			279	297				712
29				978				490				298				713

Notes: Own illustration. This table shows the own supply and demand estimates. Years refer to the first year of the marketing season, i.e. 2011 refers to 2011/2012. The calculation is discussed in section 2.6. If one or two of the sources had missing values, the result is also reported as missing value. The Report-Nr. refers to the number of the AMIS Market Monitor (AMIS 2015).

8.2 Appendix for chapter 3

The results depend not only on the model parameters but also on the parameters which are chosen to solve and simulate the model (lower half of Table 3.1). In order to test the precision of the results, different values were explored. This appendix first presents how the precision of the numerical solution depends on the grid size and second how the precision of the estimated parameters depends on the number of simulated shock realizations.

The highest and lowest grid points need to be chosen such that the simulated realizations do not exceed these values. In order to find the perfect foresight solution, a time horizon of 5 periods before convergence to the steady state turned out to be sufficient for all cases. With the solution methods detailed in Table 3.1 all models could be solved. In order to evaluate the necessary grid points (and therefore grid density), the grid points for each dimension were varied from 10 to 120. Figure 8.1 shows the absolute and relative deviation of the response variable for the different grid sizes from 10x10 to 80x80 with 120x120 as reference case for comparison. While a low grid density leads to less precision, high grid densities require a lot of computation time.

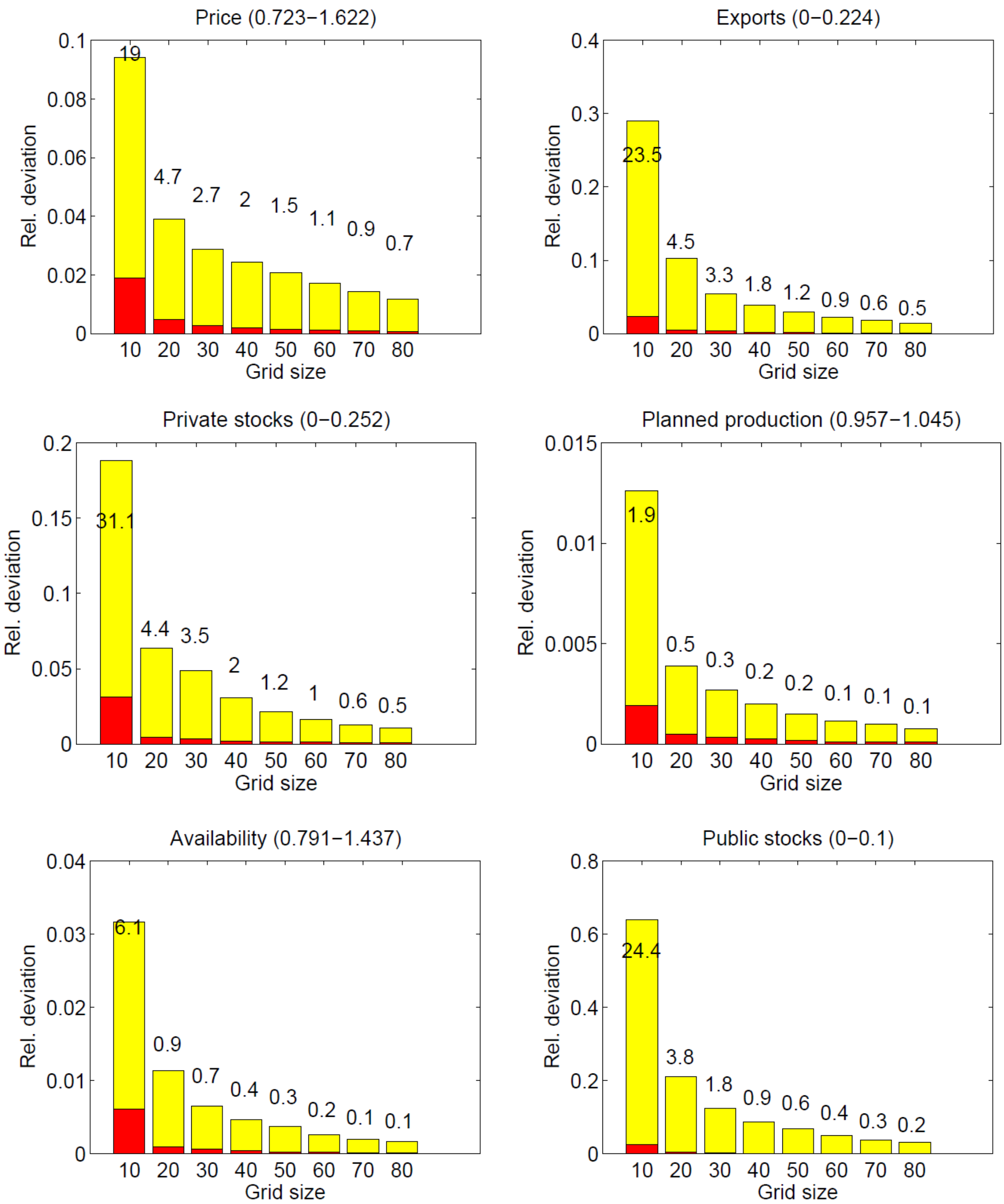


Figure 8.1: Testing the grid density

Notes: Own illustration. Relative deviation for the availability, public stocks, private stocks, planned production, price and exports in/from country A. The yellow bars show the maximal relative deviation, the red bars the mean relative deviation of the respective grid size compared to the reference case with a grid size of 120x120. The numbers above the graphs are the mean absolute deviation divided by 1000. The range of the respective response variables is indicated in the headlines after the variable name.

To compute these results, 900,000 realizations of the shock variable were used in order to guarantee a minimal bias from the simulations. The yellow bars show the maximal deviations, the red bars the mean deviations which are, divided by 1000, also indicated by the numbers above the bars. To ensure that the differences are not the result of different shocks, the same realizations of the shocks were used for all scenarios. It can be seen that even with very low grid sizes, the mean deviation is very small. However, the maximal deviation remains significant for some response variables if the grid densities are too low. A grid size of 50x50 was chosen which offers a high and sufficient precision while not requiring excessive computation times.

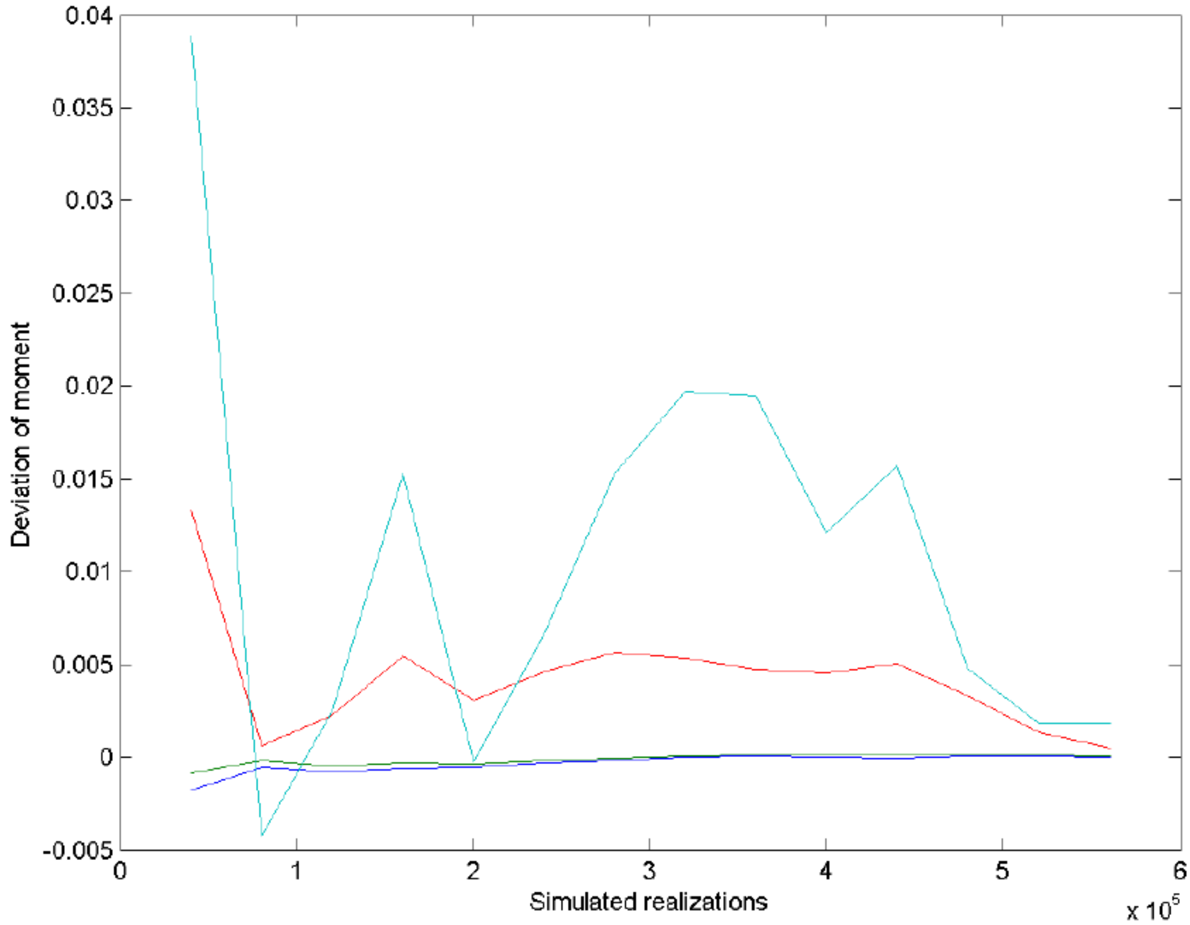


Figure 8.2: Dependency of the price moments on simulated realizations

Notes: Own illustration. The deviation of the mean (dark blue), the standard deviation (dark green), the skewness (red) and the kurtosis (light blue) of the price is shown for different amounts of simulated realization ranging from 20,000 to 580,000 with the simulation of 600,000 realizations as reference case. For more than 100,000 realization, the mean and SD are below 0.0006, the skewness below 0.006, and the kurtosis below 0.04, respectively.

Imprecise results may not only be the outcome of a low grid size but also of using only few stochastic realizations of the shocks for estimating the moments, percentiles, and frequencies of the response variables. Hence, the deviations of the moments and percentiles depending on the simulated realizations are calculated and illustrated in figures Figure 8.2 and Figure 8.3, respectively. The first and second moments can already be estimated with a high precision when few realizations are used, whereas skewness and in particular kurtosis still differ significantly for many realizations. Percentiles appear to be rather precise if at least 100,000 realizations are used. Only the 99.9th percentile shows a minor acceptable deviation of less than 0.0035. Overall, it is therefore concluded that simulating 120,000 realizations provides a sufficient level of precision. This number is split up into 600 cases starting from the steady state which are in each case followed by 200 stochastic realizations.

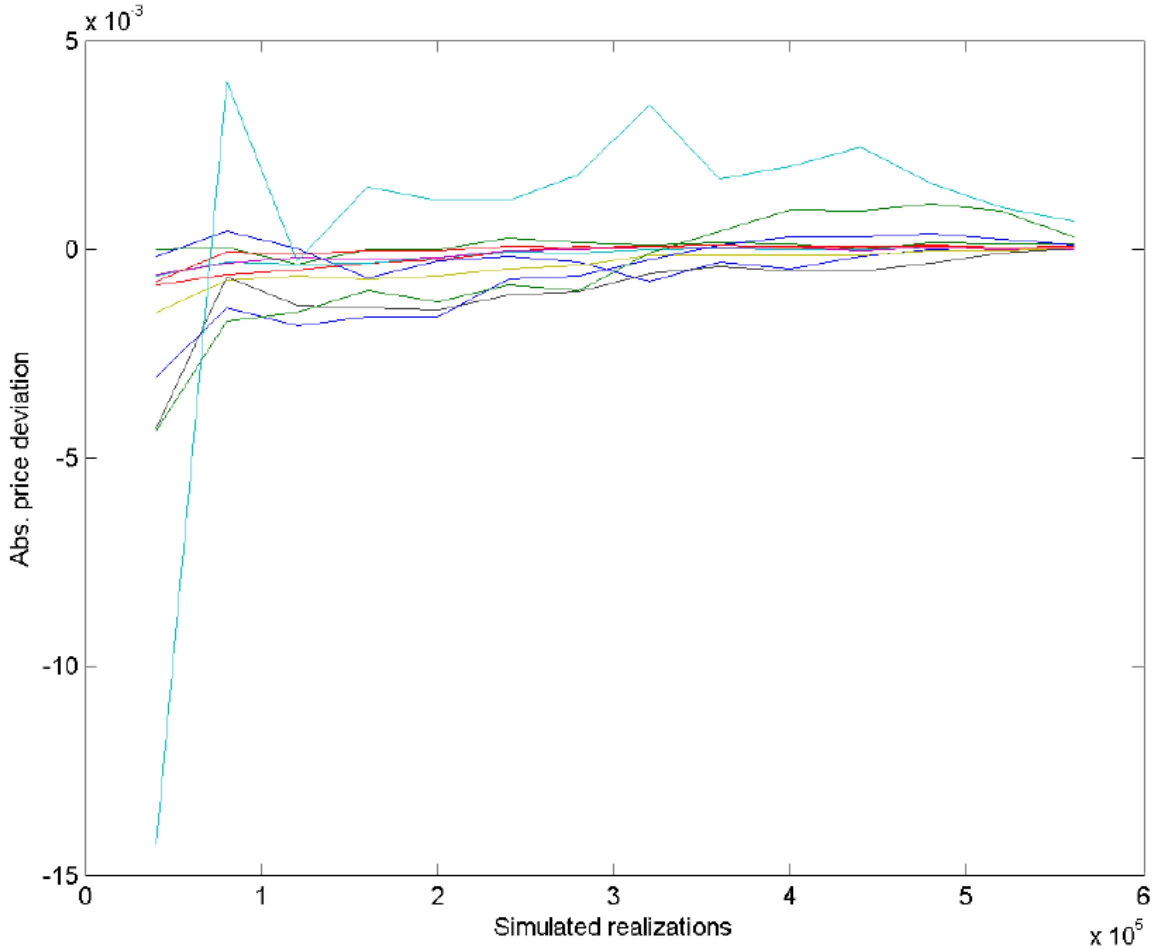


Figure 8.3: Dependency of different price percentiles on simulated shock realizations

Notes: Own illustration. The deviation of different price percentiles (0.1, 1, 5, 10, 25, 50, 75, 90, 95, 99, 99.9) is shown for different amounts of simulated realization ranging from 20,000 to 580,000 with the simulation of 600,000 realizations as reference case. The absolute deviation of all percentiles is below ±0.002 for more than 100,000 realizations except for the 99.9 percentile (light blue) whose deviation is below ±0.0035.

8.3 Appendix for chapter 5

The following two tables show the regression results for the non-extended data, i.e. for the years from 1990 to 2014 for which the October stocks are available from the FCI.

Table 8.2: Public rice stock regression using only available FCI October stock data

	(1)	(2)	(3)	(4)
Estimation	Levels	Levels	FD	FD
L.Public Stocks	.666***	1.18**	.447	.969**
	(.105)	(.45)	(.305)	(.391)
MSP	1.2***	1.03**	1.33***	1.22***
	(.414)	(.485)	(.308)	(.409)
Private Supply	.241	.454***	.187	.362**
	(.158)	(.152)	(.163)	(.141)
Export Ban	.039**	.032**	.042*	.04**
	(.017)	(.012)	(.02)	(.018)
Above Buffer		.984		.979
Norm		(.73)		(.657)
Constant	-.535**	-.774***	1.6e-03	2.1e-03
	(.241)	(.195)	(8.1e-03)	(8.4e-03)
BIC	-85.8	-86	-70.9	-71.3
R2	.802	.828	.456	.533
Observations	24	24	23	23

Notes: Own illustration. Robust standard errors in parentheses;* p < 0.10, ** p < 0.05, *** p < 0.01

Table 8.3: Private rice stock regression using only available USDA or FAO data

	(1)	(2)	(3)	(4)
Private Stock Data	USDA	USDA	FAO	FAO
Estimation	IV-Levels	IV-FD	IV-Levels	IV-FD
Public Stocks	-.472***	-.343***	-.627***	-.145
	(.106)	(.099)	(.197)	(.177)
Supply	.289***	.226***	.41**	.31***
	(.101)	(.063)	(.177)	(.069)
Export Ban			.038	
			(.024)	
Constant	-.244**	-2.7e-03	-.374*	1.0e-03
	(.113)	(4.1e-03)	(.202)	(5.0e-03)
UI: LM / stat	7.14	3.85	6.23	2.5
UI: LM/ p	.028	.05	.044	.287
WI: F stat	39.5	17.7	6.63	6.72
BIC	-102	-107	-56.7	-55.9
R2	.237	.419	.349	.592
OI: Hansen J/stat	.454	0	.038	2.19
OI: Hansen J/p	.5		.846	.139
First-stage R2	.698	.32	.655	.288
First-stage F	56.1	9.34	27.8	7.74
Observations	24	23	16	15

Notes: Own illustration. Robust standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01. Statistics used as in Table 5.3.

8.4 Appendix for chapter 6

The following graphs show the influence of the price over time, i.e. the evolution of the p-value of the price and other variables. This also indicates the robustness of the estimation.

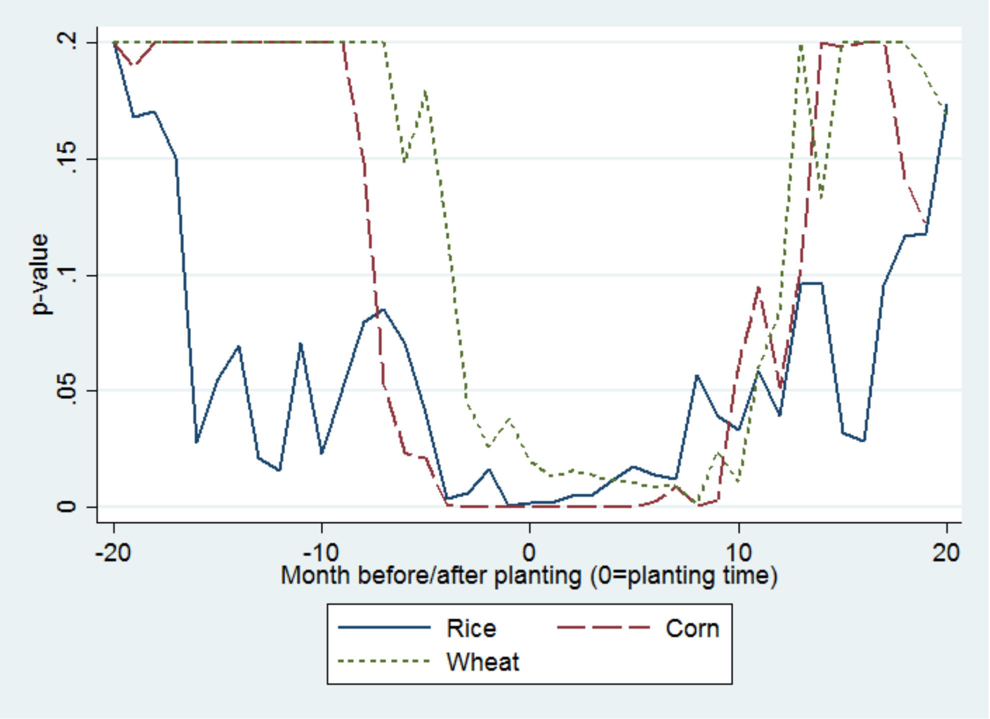


Figure 8.4: Significance of the wholesale prices over time (difference GMM estimator).
(Own illustration)

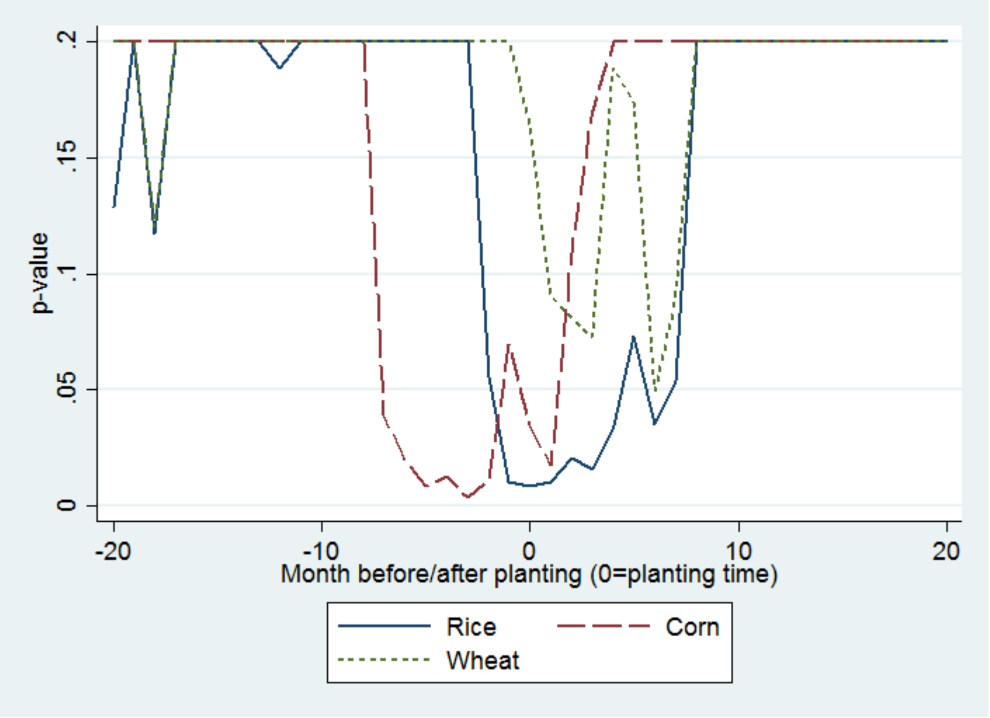


Figure 8.5: Significance of the wholesale prices over time (system GMM estimator).
(Own illustration)

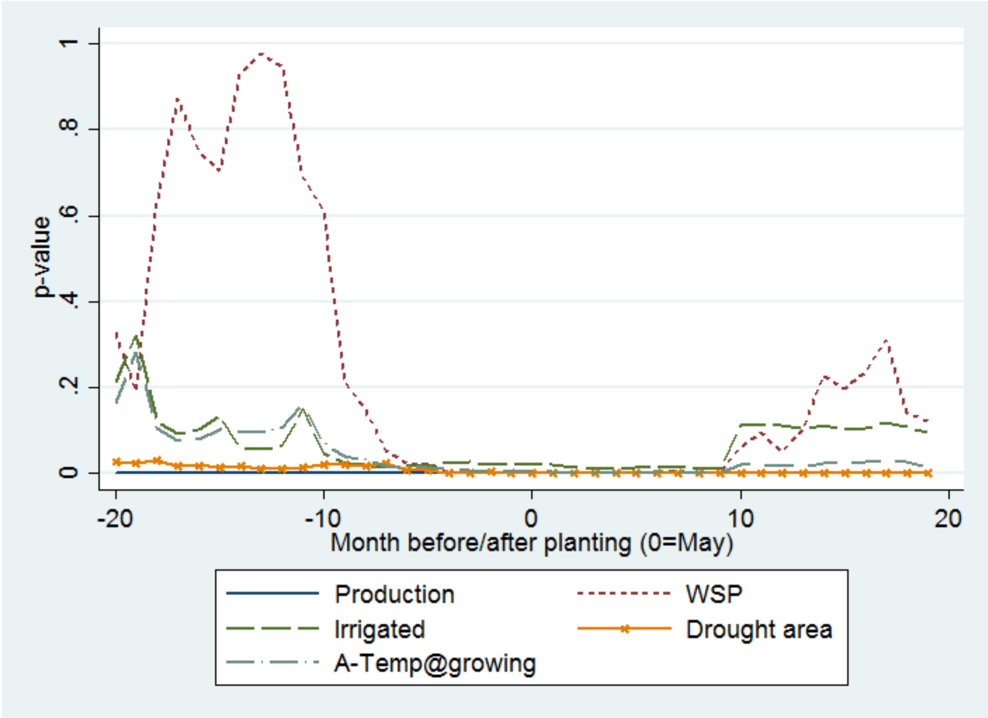


Figure 8.6: Significance of explanatory variables over time (difference GMM estimator)

Notes: Own illustration. Results are for the second specification for corn. Not all explanatory variables are shown to maintain recognizability and the prices are the only variables which were varied over time.

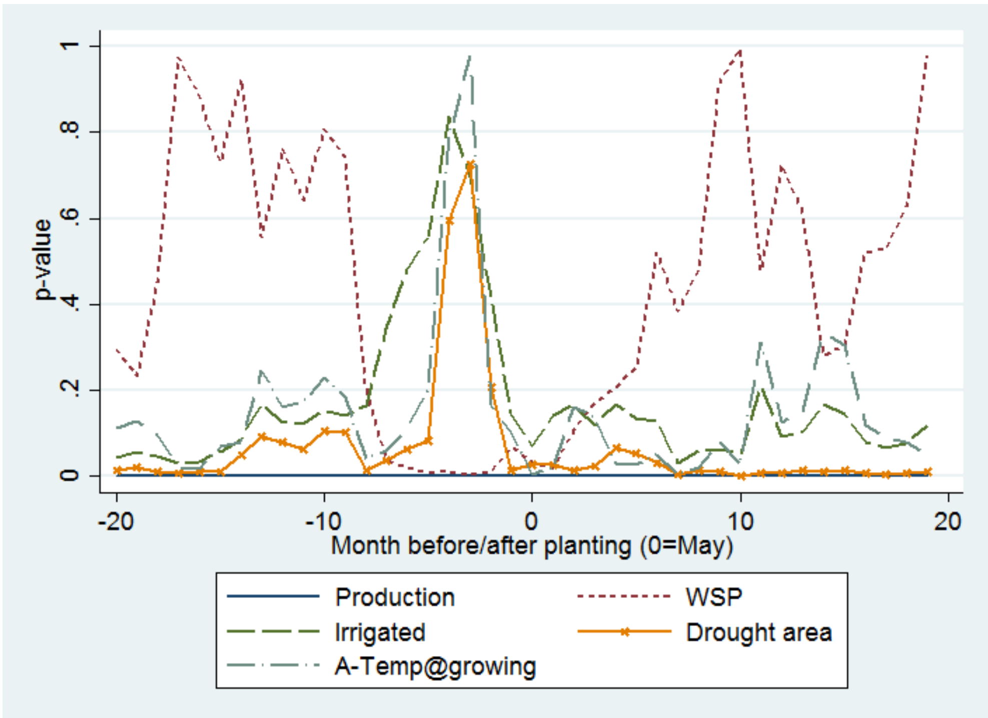


Figure 8.7: Significance of explanatory variables over time (system GMM estimator)

Notes: Own illustration. Same notes as for Figure 8.6 apply.