Globally Distributed Production and the Pricing of CME Commodity Futures

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Abstract

I investigate how local supply shocks in the globally distributed production of commodities are incorporated into CME futures prices. I exploit that the soybean market share of the US (Argentina) decreased (increased) between 1996 and 2010, and use rain, which tends to increase output, as a source of exogenous supply shocks. I find a significantly negative response of CME soybean prices to daily rain across regions and time. Moreover, the impact of local rain in the CME price is approximately linear in the time-varying local share of global output. CME traders seem to aggregate supply in a globally integrated manner therefore US based hedgers are increasingly exposed to shocks abroad.

Keywords: Commodities; International asset pricing; Futures; Emerging Markets.

JEL codes: G13; G14; F36; Q11.

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1. Introduction

The mechanism of aggregation of various sources of fundamental information into a single price is a central question in asset pricing. In this paper I investigate how geographically distributed supply shocks are incorporated into the prices of the most liquid agricultural commodity futures, namely those traded at the Chicago Mercantile Exchange.

The distributed nature of agricultural commodity production leads to some natural questions regarding the formation of CME prices. Do supply shocks at locations far from the US Midwest matter as much as those close to Chicago? How is the size of local production related to the response of the CME price to local events? How is the rise of emerging economies in the global production of commodities represented in the dynamics of CME prices?

Beyond their academic interest, answers to these questions are relevant for policy makers and risk managers. I find, in particular, that CME soybean futures prices have become increasingly sensitive to supply shocks outside of the US. Therefore, US based firms that hedge their sales and purchases by trading CME contracts are doing so at price levels that are increasingly dependent on supply shocks outside of the US.

I explore the broad questions outlined above by focusing on the global soybeans market, which is particularly convenient for three reasons. First, local summer rain precipitation tends to increase local soybean output. Therefore rain is an exogenous source of local supply shocks. Second, the US Midwest and the central region of Argentina concentrate about 45% of the global production of soybeans. Spatial concentration is convenient because it amplifies the impact of local events on global prices [1]. Finally, the market shares of these dominant regions have varied over the last fifteen years due to strong output growth in Argentina and mild relative decline in the US. This allows me

[1] Brazil, the second largest producer of soybeans, is not included in the analysis in this paper for reasons discussed in Section 2.

to track how the response of the CME price to local supply shocks has evolved following changes in market shares. In summary, the combination of these three elements allows me to identify how the price of soybeans at the CME responds to regional supply shocks and to relate the price impact of rain to shares of global production.

Soybeans are grown from late spring to early fall, so I define the *extended summer* as May-October for the US Midwest and November-April (of the following year) for Argentina. Output at harvesting time is most sensitive to rain during the *midsummer* months, defined as July and August for the US Midwest, and January and February for Argentina. I find that in the period 1996/7 to 2002/3 one inch of midsummer rain over the US Midwest caused, in average, a 5.1% decrease in the CME soybean price after controlling for changes in the the Oil price and local temperature among other factors. During that period, one inch of midsummer rain over the central region of Argentina had no significant impact on the CME price. In this period, the production of soybeans in the US Midwest accounted for 30.8% of global annual production, and the share of global output grown in the central region of Argentina was only 12.3%. In the period 2003/4 to 2010, coincident with a decrease of the US Midwest share to 23.6% and an increase of Argentina's core region share to 16.5%, I find that one inch of midsummer rain over the US Midwest caused a 1.8% decrease in the relevant CME soybean price while the same amount of rain in Argentina led to a 1.6% CME price decrease. For proper context, midsummer rain precipitation in any of these two regions has historically been close to 10 inches. Therefore, one inch of rain is biologically important and leads to the economically significant price impact that I estimate. Analogous estimates of rain's impact over a partition of the 1996-2010 dataset on biennial periods shows that the magnitude of local rain's impact on price, across periods and regions, is close to linearly related to the corresponding local share of global production.

I show that these empirical findings are generally in agreement with the predictions of a very simple model of distributed commodity production that assumes that an additional unit of supply anywhere in the world has the same impact on the CME price. My empirical results suggest that traders at the CME incorporate information about distributed supply shocks in a manner that is roughly consistent with a globally integrated market for soybeans and indifferent to the geographical origin of supply. Therefore, as output from Latin America has recently grown relative to that from the US, risk managers using CME contracts are hedging their output at prices increasingly influenced by events outside of the US.

The setting chosen in this paper to explore the spatial aggregation of supply shocks into a single asset price is economically important. The growing weight of developing economies in the global economy is one the main economic developments of the last decade. Between 2002 and 2009, the GDP of developed economies including, among others, the Euro area, Japan, the UK and the US, grew at an average annual rate of 1.3%. During the same period, developing economies including China, India, Argentina and Brazil, achieved an annual rate of growth of 5.8% (United Nations' *World Economic Situation and Prospects 2011* [2]). Some of the most important developing economies are heavily dependent on commodity markets. Argentina and Brazil are leading exporters of agricultural commodities including soybeans, corn, wheat, cotton and coffee. Brazil is also the third global producer of iron ore, behind China and Australia. Russia is the second world producer of oil and a large presence in the metals market. China is a leading commodity importer and is expected to grow its influence in the near future.

Commodities are traded globally through financial and physical contracts. For historical and institutional reasons the most important derivatives market for agricultural commodities is the Chicago Mercantile Exchange (CME), which merged with the Chicago Board of Trade (CBOT) in 2007. Futures contracts for soybean and derived products

[2] http://www.un.org/en/development/desa/policy/wesp/

traded at the CME are very liquid. CME quoted prices are widely followed by soybean farmers, traders, hedgers and speculators around the world. CME contracts are also used by investors, specialized hedge funds and index funds increasingly interested in gaining exposure to commodity markets as an asset class (Tang and Xiong (2009)).

This paper is related to three strands in the literature. First, the question of how futures prices reflect fundamental information has been central in the asset pricing literature in general and commodities in particular. An incomplete list of related works includes Routledege et al. (2000), Casassus and Collin-Dufresne (2005), Kogan et al. (2009), Liu and Tang (2010) and Elder et al. (2012). Within this line of work, this paper is closest in spirit to a few studies linking weather related information and asset prices. Roll (1984) was among the first to study the effect of weather in agricultural futures prices by evaluating the impact of rain and temperature on the production of orange juice in Florida. He found surprising little explanatory power for meteorological variables. His conclusions were then revised by Boudoukh et al. (2007), who found strong explanatory power for a nonlinear effect of temperature on orange juice prices due to negative supply shocks caused by freezing events. As it is the case for soybeans, oranges for juice production are heavily concentrated in Florida and the state of Sao Paulo in Brazil. Boudoukh et al. (2007) provided some anecdotal evidence about the importance of news about Brazilian production reported in the Wall Street Journal, and performed a correlation analysis between US and Brazilian production and exports based on annual data. They found evidence that Brazilian and Florida oranges are substitutes but did not perform a direct analysis of Brazilian supply shocks on US prices. In contrast, this paper analyzes the behavior of CME prices using an econometric methodology that treats the US and Argentina symmetrically and relies on high frequency local weather data. Fleming et al. (2006) studied the interplay between the flow of information originated in weather dynamics and changes in commodity prices, including soybeans, by analyzing variance ratios for weather sensitive markets. They found that weather related information is significant in generating price volatility. The impact of changes in expected supply and demand into agricultural commodity prices was studied by Isengildina-Massa et al. (2008) who estimated the response of CME soybean futures prices to the widely followed World Agricultural Supply and Demand Estimates (WASDE) released monthly by the US Department of Agriculture. They found a significant increase in price variance on the dates of a WASDE release. Their work, however, is silent about the mechanism of aggregation of supply shocks from different geographical locations. Moreover, the WASDE report suffers from some weaknesses. First, it is computed by the USDA using fundamental sources of information that might also be processed independently by sophisticated market participants and incorporated into prices, to same extent, prior to the release of the report. In this paper I use rain precipitation that is truly unanticipated information beyond the horizon of weather forecastability. Second, the WASDE report is released monthly, while rain precipitation is available with daily frequency, potentially allowing for more precise estimates.

A second strand of the literature related to this paper is existing work on financial integration. Most work in this literature has focused on the integration of financial markets, in the sense that similar risks in equities or bonds, in different countries, should be priced in a similar manner when capital is allowed to flow freely across borders (Errunza and Losq (1985), Bekaert and Harvey (1995), Bekaert et al. (2007)). Work on financial integration on commodities has explored the notion that the same physical asset should be priced consistently at different locations after taking into account transportation costs, tariffs, and other frictions. Findlay and O'Rourke (2003) analyzed major trends on commodity market integration across a 500 year span, Fung et al. (2010) studied the flow of information in aluminum and copper markets between the New York Mercantile Exchange and the Shanghai Futures Exchange, Chng (2009) studied the joint dynamics of seemingly unrelated commodities used by the same industry and Casassus et al. (2011) investigated the joint dynamics of commodity prices linked through economic relationships such as complementarity and substitution. In this paper, rather than asking how prices and returns are aligned across borders or markets, I ask how local production information is incorporated into a single price at the CME market. In other words, I ask how apparently similar risks (supply shocks in various regions) are incorporated into a single price that serves as a global benchmark, paying special attention to the relevance of regional shares of global production.

Finally, this paper belongs to a growing list of empirical studies on commodity markets. The large increase in commodity prices between 2004 and 2011, briefly interrupted by the financial crisis of 2008, has revitalized a large literature on the dynamics and drivers of commodity prices beyond weather related variables. Recent contributions to this extensive literature include the work by Frankel and Rose (2009) who proposed a model to determine commodity prices, including soybeans, and found that inventory levels and the slope of the forward curve are most important in explaining observed prices. Gorton et al. (2007) studied a comprehensive data set on 31 commodity futures and physical inventories between 1969 and 2006 and identified a central role for inventories in the determination of the convenience yield and risk premia. Roberts and Schlenker (2010) exploited exogenous weather related supply shocks to estimate demand and supply elasticities of agricultural commodities, and they used their estimates to evaluate the impact of biofuels on food prices. Earlier relevant work also includes Deschenes and Greenstone (2007), on the economic impact of yearly varying agricultural output in response to weather fluctuations in the context of climate change. Focusing on soybeans, Geman and Nguyen (2005) found that inventories are inversely related to price volatility. Borensztein and Reinhart (1994) used quarterly macroeconomic data from 1970 to 1992 to estimate the impact of supply and demand dynamics on commodity prices, including effects due to structural changes in Eastern Europe.

The paper is structured as follows: in Section 2, I describe the structure of the global soybean market. In Section 3, I present a simple model of a globally integrated economy in which regional market shares are linearly related to the sensitivity of the CME price to regional rain. This model is estimated using the econometric approach described in Section 4, applied to the data presented in Section 5. My empirical results are in Section 6 and conclusions in Section 7.

2. The Global Soybean Market

Soybeans and derived products are very important protein sources of agricultural origin. The so-called soybean complex includes soybeans, soybean meal primarily used for animal feeding, and soybean oil. Crushing a ton of soybeans yields approximately 0.73 tons of meal and 0.18 tons of oil. The soybean market has grown very strongly over the last twenty years. Annual production in the World, the US, and Argentina, during the period 1996-2010, measured in millions of metric tons per year, and the corresponding shares of global production are reported in Table I. In 1997 Argentina grew 8% of global production, and this became 19% in 2011. During the same period, the relative contribution of the US production to global output fell from 49% to 35%. Table I also shows that yields have been similar in both countries and have remained relatively stable in time.

Figures 1 and 2 show soybean and soybean meal exports from various regions. Argentina exports the bulk of its production in the form of soybean meal and soybean oil and only a small fraction of its production in the form of beans. The US exports mostly in the form of beans. Domestic consumption of soybean related products is significant in the US and very small in Argentina. Table I, Figure 1 and Figure 2 are composed using information from the USDA *Oilseeds Reports* for December 2006, December 2010 and May 2011 [3]. The price of a metric ton of soybeans at the CME on August 2011 was approximately 500 US dollars. For a global production of 260 million metric tons this implies a market value of roughly USD 130 billion.

Argentina and Brazil, the second largest soybean producer after the US, experienced in recent decades similar rates of growth. I focus in this paper on the impact of rain in the central region of Argentina and the US Midwest because these soybean producing regions are biologically similar in the impact of precipitation on soybean yields. The main soybean producing regions in Brazil are the states of Goias, Matto Grosso, Parana, and the northern part of the state of Rio Grande do Sul, which have historically received summer rainfall exceeding that in Argentina and the US Midwest by approximately 50%, therefore making its output potentially less sensitive to rain. More importantly, the precipitation data used in this paper for Argentina and the US Midwest was gathered from the database at the National Climatic Data Center (NCDC) administered by the National Oceanic and Atmosphere Administration (NOAA). This source, which reproduces information submitted by official local meteorological organizations, exhibited severe gaps between 2000 and 2004 for Brazilian weather stations. Although Argentina and Brazil are neighboring countries in South America, the main soybean producing regions in Brazil are between 500 and 1500 miles away from the soybean producing region in central Argentina, therefore affected by different high frequency weather events.

Table II reports annual soybean production of individual provinces in Argentina. The most important soybean producing region in Argentina is conformed by the provinces of Buenos Aires, Santa Fe, Cordoba and Entre Rios, located at the center of the country. Between 1997 and 2003 this region produced an average of 89% of national output, a ratio that decreased slightly to 87% for the period 2004-2010 (Production information at

[3]http://www.fas.usda.gov/oilseeds_arc.asp.

the province level for the 2011 harvesting season was not available at the time of writing this paper). Table II also shows annual regional yields (in tons per hectare). Table III shows annual output for states in the US Midwest, defined as the region including Illinois, Indiana, Iowa, Missouri, Minnesota, Nebraska, and Ohio. The US Midwest produced 72% of US soybeans during 1996-2002 and 68% of US soybeans during 2003-2009. Table III also reports annual regional yields.

Soybeans are grown especially during the summer and more generally from late spring to early fall. This ranges from May to October in the northern hemisphere, and from November to April in the southern hemisphere. Soybean supply at harvesting time is determined by the sum of production in the current season and existing stocks from previous years. Soybeans are usually consumed or processed in the year following harvest. The highest ratio of existing stocks in the US at the beginning of the year to subsequent yearly production for the period 1997-2010 was 22%, and less than 10% for most years. The same ratio for Argentina in the same period of time was never above 18% and also less than 10% for most years. (Tables 21 and 23 in the *Oilseeds Report* of December 2010, USDA). Therefore supply is essentially provided by newly harvested soybeans.

Production is determined by two factors: the area of land allocated each year to growing soybeans, and the yield per acre which measures output per unit of land. The year to year variation in the area of land allocated to soybeans has an impact on supply but it is a low frequency variable because it is determined only once per year and the estimation of its effect on prices is complicated by its endogeneity. Yield depends on the available growing technology, quality of the soil, use of fertilizers and herbicides and, most crucially, water intake. Irrigation technology is expensive and not used in the soybean growing regions in Argentina. Irrigation in Midwest states is reported in Table IV. The proportion of irrigated land is negligible for every state, perhaps with the exception of Nebraska. I could not determine how much of the irrigated land in Nebraska is allocated to growing soybeans, but the fact that irrigation covers only 15% of the state and that Nebraska has historically produced about 10% of Midwest output leads me to assume in the remainder of the paper that water intake for growing soybeans in the US Midwest is essentially provided by rain.

Tannura et al. (2008) showed a significant and positive correlation between summer rain precipitation and soybean yields in the states of Iowa, Illinois and Indiana. The association was found to be particularly strong for the months of July and August, a period I call midsummer. I provide in this paper additional empirical support for the strong link between midsummer precipitation and soybean output for Argentina and the US Midwest. This biological link between exogenous rain and output will be exploited in this paper to identify the sensitivity of soybean prices to supply shocks. From an econometric perspective, the availability of daily recordings for a large number of spatially distributed weather stations, leading to many data points per season, makes rain a very convenient variable to study the impact of exogenous changes in expected supply on the price of soybeans. Tannura et al. (2008) also found that temperature fluctuations lead to variability in output in the US Midwest, therefore in my econometric analysis I also include temperature as a potential source of price variations.

Commodities are traded physically by producers, consumers and big trading houses such as Cargill, Bunge, Noble and Glencore. Physical transactions are associated to a variety of shipping routes across the globe. Freight-on-board (FOB) prices for spot physical delivery at certain shipping terminals are quoted on a daily basis in the over-the-counter market for the Gulf of Mexico and several ports in Latin America. These FOB prices are usually positively correlated with the CME price but differ from it by a stochastic basis driven by seasonal and technical factors. Hedging and speculation on commodities is mediated by financial contracts. The prices of the most liquid contracts for soybeans, traded at the CME, are widely followed by soybean traders around the world. Soybeans underlying CME contracts are delivered at expiration in physical form at warehouses in the US Midwest, although most futures contracts are canceled before expiration.

3. The Model

The main contribution of this paper is the family of empirical results in Section 6, which explicitly link regional rain with CME price changes, and rain's impact on prices with global market shares of production. Yet, in order to understand the significance of these empirical results I find it helpful to introduce a highly stylized model of distributed production under exogenous weather shocks. In the remainder of this Section I will focus explicitly on the effect of rain on prices, although temperature fluctuations will receive equal attention in the econometric tests of the model.

3.1. Rain and supply

A large number of firms produce soybeans in Argentina and the US Midwest and sell their output in a competitive global market. Deodhar and Sheldon (1997) studied the degree of competition in the soybean meal export market using data with annual frequency from 1966 to 1993 and found that the market was very close to perfectly competitive. Beans are grown during the extended summer season lasting from the beginning of May to the end of October in the US Midwest, and from the beginning of November to the end of April in the central region of Argentina. Soybeans are also grown in other regions that are geographically distant from those I focus on, therefore unaffected by rain precipitation in the US Midwest and the central region of Argentina.

This is a model for a single growing season. The amount of land, A_0^{Region}, allocated to growing soybeans is set at $t = 0$. Let T be the harvesting time at the end of the growing season, measured in days. The terminal yield obtained at harvesting time is most sensitive to rain during the midsummer months of July and August in the US and January and February in the central region of Argentina. Let T_{start} and T_{end} be the start and the end of the relevant rain period within a growing season, so that $0 < T_{start} < T_{end} < T$.

Regional output is harvested at T in the region that is currently active and added to typically small existing stocks, for final regional supply $Q_{Supply,T}^{Region}$ measured in metric tons. Land, terminal yield Y_T^{Region}, and output are related through

$$Q_{Supply,T}^{Region} = A_0^{Region} Y_T^{Region}. \tag{1}$$

Total global supply available at T is

$$Q_{Supply,T}^{World} = Q_{Supply,T}^{Midwest} + Q_{Supply,T}^{Argentina} + Q_{Supply,T}^{Rest}. \tag{2}$$

On the $i-$th trading day, $i = T_{start}, ..., T_{end}$ let I_i be the information available to CME market participants. Expected regional soybean supply at harvesting time T, conditional on the available information, is $E[Q_{Supply,T}^{Region}|I_i]$.

Uncertainty about supply at harvesting time is a function of the yield per unit of land, which depends on technology and water intake. In the absence of irrigation, water intake is provided exclusively by rain. Let R_j^{Region} be the amount of rain fallen on day j over a region of interest and

$$R^{Region} = \sum_{j=T_{start}}^{T_{end}} R_j^{Region} \tag{3}$$

the total precipitation during the midsummer period. Based on the positive relationship between precipitation and yields documented by Tannura et al. (2008) I postulate a linear relationship between midsummer rain and terminal output at harvesting time.

$$Q_{Supply,T}^{Region} = Q_{Supply,0}^{Region} + \gamma^{Region} Q_{Supply,0}^{Region}(R^{Region} - \bar{R}^{Region}) \tag{4}$$

where $Q_{Supply,0}^{Region}$ is the output at T expected at $t = 0$ conditional on long term historical yield $\bar{Y}^{Region}$ known at the beginning of the growing season, and $\bar{R}^{Region}$ is the historical average midsummer precipitation. The positive coefficient γ^{Region} is the relative sensitivity of regional yield to total rain precipitation during this period. Because the amount of land allocated to soybeans is fixed within a growing season (4) is equivalent to

$$Y_T^{Region} = \bar{Y}^{Region} + \gamma^{Region} \bar{Y}^{Region}(R^{Region} - \bar{R}^{Region}) \tag{5}$$

Expectations of terminal output are updated during the rain period reflecting changes in expected rain precipitation. Taking conditional expectations in (4) I write

$$E[Q_{Supply,T}^{Region}|I_i] - E[Q_{Supply,T}^{Region}|I_{i-i}] = \gamma^{Region} Q_{Supply,0}^{Region}(E[R^{Region}|I_i] - E[R^{Region}|I_{i-1}]). \tag{6}$$

A precipitation forecasting technology such as that provided by the National Weather Service is available to market participants on each day. If this technology, conditional on I_i, has perfect predictive capability for up to τ days beyond $t = i$ and it is completely unskilled beyond that horizon, then I can write

$$E[R^{Region}|I_i] = \sum_{j=T_{start}}^{i+\tau} R_j^{Region} + ((T_{end} - T_{start}) - i - \tau)\frac{\bar{R}^{Region}}{T_{end} - T_{start}} \tag{7}$$

because daily rain that is beyond τ days into the future is unpredictable therefore its expectation is $\frac{\bar{R}^{Region}}{T_{end}-T_{start}}$, and rain that has already occurred, or that will occur in a horizon shorter than τ has already been incorporated with certainty into the expectation of future precipitation. Therefore,

$$E[R^{Region}|I_i] - E[R^{Region}|I_{i-}] = R^{Region}_{i+\tau} - \frac{\bar{R}^{Region}}{T_{end} - T_{start}}. \tag{8}$$

It is learning about rain at the prediction horizon that drives the daily change in expectations in (8). In a more realistic setting, weather forecasting skill is less than perfect and certainty about rain on a given target date develops gradually as time evolves towards the target date. Bickel et al. (2011) evaluated the accuracy of Probability of Precipitation (PoP) forecasts generated by the National Weather Service dependent from NOAA, the Weather Channel, and CustomWeather, which are available to market participants at low or no cost. They considered forecasts at 753 location in the US and found evidence of significant forecasting skill for up to a 96 hour horizon for all weather forecast providers. This leads me to postulate

$$E[R^{Region}|I_i] - E[R^{Region}|I_{i-1}] = \frac{1}{\tau}\sum_{j=1}^{\tau} R^{Region}_{i+j} - \frac{\bar{R}^{Region}}{T_{end} - T_{start}} + \eta, \tag{9}$$

where η is a generic random error uncorrelated with $\sum_{j=1}^{\tau} R^{Region}_{i+j}$, and $\tau = 4$ days. From (6) and (9) it follows that the impact of rain in expected supply is

$$E[Q^{Region}_{Supply,T}|I_i] - E[Q^{Region}_{Supply,T}|I_{i-1}] = \gamma^{Region} Q^{Region}_{Supply,0}\left(\frac{1}{\tau}\sum_{j=1}^{\tau} R^{Region}_{i+j} - \frac{\bar{R}^{Region}}{T_{end} - T_{start}}\right) + \eta \tag{10}$$

for a rescaled error term η. An alternative to the approach described above consists in using actual weather forecasts rather than subsequent precipitation. However, there is no publicly available record of historical weather forecasts for Argentina going back as far as 1996. Regarding US weather forecasts, Chincarini (2011) reports that archived forecasts for the National Weather Service Model Output Statistics begin in September 2005.

3.2. Supply and prices

Let P_T be the soybean spot price at the end of the current growing season and let $Q^{World}_{Demand,T}$ be global demand at T. I adopt a standard constant elasticity demand curve

$$Q^{World}_{Demand,T} = aP^b_T, \tag{11}$$

with price elasticity of demand $b < 0$, and assume that this remains unaffected by local regional rain during the growing season. This is plausible because soybeans are used primarily for the delayed production of soybean meal and soybean oil and sold for later consumption at widely spread locations (often overseas) that are far from the relatively small producing regions. In addition, the fact that several months are needed to grow soybeans leads me to postulate that $Q^{World}_{Supply,T}$ is inelastic in the short run with respect to prices. From (11), equilibrium at T implies

$$aP^b_T = Q^{World}_{Supply,T}. \tag{12}$$

Taking conditional expectations with respect to the information available on consecutive days in the growing season, summing over regions, and combining with (10) I obtain

$$E[aP_T^b|I_i] - E[aP_T^b|I_{i-1}] = \sum_{Regions} \gamma^{Region} Q_{Supply,0}^{Region} (\frac{1}{\tau} \sum_{j=1}^{\tau} R_{i+j}^{Region} - \frac{\bar{R}^{Region}}{T_{end} - T_{start}}) + \eta^{Region}. \tag{13}$$

Next, a standard linearization of P_T^b around $E[P_T|I_0]$ in (13) leads to

$$\frac{E[P_T|I_i] - E[P_T|I_{i-1}]}{E[P_T|I_{i-1}]} \approx \frac{1}{b} \frac{1}{E[Q_{Supply,T}^{World}|I_{i-1}]} \sum_{Regions} \gamma^{Region} Q_{Supply,0}^{Region} (\frac{1}{\tau} \sum_{j=1}^{\tau} R_{i+j}^{Region} - \frac{\bar{R}^{Region}}{T_{end} - T_{start}}) + \eta^{Region} \tag{14}$$

The analysis so far has related expected spot price at harvesting time T with expected future rain. I now make the connection with the CME futures price available at $t = i$. Let P_i^T be the CME soybean future price observable at $i \leq T$ associated with a CME contract expiring at the end of the current growing season. Let the future price be the expected spot price at expiration plus a small deterministic risk premia Y_i

$$P_i^T = E[P_T|I_i] + Y_i. \tag{15}$$

From (14) and (15) I arrive to

$$\frac{P_i^T - P_{i-1}^T}{P_{i-1}^T} \approx \frac{1}{b} \sum_{Regions} \gamma^{Region} S^{Region} (\frac{1}{\tau} \sum_{j=1}^{\tau} R_{i+j}^{Region} - \frac{\bar{R}^{Region}}{T_{end} - T_{start}}) + \eta^{Region} + dt \tag{16}$$

where $S^{Region} \equiv \frac{Q_0^{Region}}{Q_0^{World}}$ is the market share of the region of interest in the global production of soybeans and dt is a deterministic trend. This is a highly stylized model for a fully integrated global market in which an additional unit of supply anywhere in the world has equal impact on the CME price traded in Chicago. Supply shocks, in turn, depend on regional rain, market shares, and physical characteristics of each region.

The first quantitative prediction of the model (16) is that excess local rain precipitation leads to a decrease in the CME future price through the combination of the price elasticity of demand $b < 0$ and the regional yield sensitivity with respect to rain $\gamma^{Region} > 0$.

The second prediction of the model (16) is that the sensitivity of the CME price with respect to regional rain is proportional to $\gamma^{Region} S^{Region}$. A special case of interest is that of physically similar regions such as the US Midwest and the central region of Argentina, with equal sensitivity γ^{Region}. In this special case, the response of the CME price to local rain is simply proportional to the local share of the global market. Rather intuitively, according to this model the CME price should be more responsive to weather events on those regions that produce larger quantities of soybeans.

The model assumes that a single variable measuring total rain over an entire region predicts regional output. This is clearly a simplification since rain and yields also exhibit variability within each region. However, attempts to identify the price impact of rain on smaller regions (e.g. individual states) are likely to be hampered by high rain correlation between neighboring states and the lesser economic importance of each individual state. The partition in two very distinct regions adopted in this paper seems appropriate to investigate the implications of globally distributed production.

The model is silent about other factors that might affect soybean prices. Tannura et al. (2008) showed that soybean output is sensitive to summer temperatures therefore I add temperature fluctuations as a control in the estimation stage. Prices are also sensitive to demand fluctuations and financial speculation. These issues, although certainly very important in the determination of commodity prices, seem at first order unrelated to the main goal of this paper, namely evaluating the impact of the distributed nature of production. Some of these effects, formally included in the noise term η in this Section, are taken into account in the empirical estimation of the model through appropriate controls.

4. The Econometric Specification

A central premise in this paper, namely that regional rain has an impact on CME prices, relies on the fact that rain is a source of exogenous supply shocks because it tends to increase yield and therefore output, as documented by Tannura et al. (2008). I begin by testing the validity of this assumption. I estimate the response of regional yield to regional rain (5) by

$$Y_i^{Region} = \alpha^{Region} R_i^{Region} + const + \epsilon_i \tag{17}$$

using annual recordings of yield Y_i^{Region} and summer rain R_i^{Region} between 1997 and 2010 for the US Midwest and the central region of Argentina. The rain variable is constructed in this exercise as the sum of total precipitation over all weather stations in the region of interest during the midsummer or extended summer of a given year. Results of this estimation confirm that rain is indeed a source of supply shocks and, by comparing $\alpha^{Midwest}$ and $\alpha^{Argentina}$, support the notion that these two regions are similar in their yield response to rain.

Next, I run daily frequency estimations of the model (16) for Argentina and the US Midwest, on periods of time with significantly different regional market shares. This allows me to identify the impact of rain in each region, and how this impact changed as the relative weight of Argentina's production increased.

The daily rain variable for any of the two regions being considered is constructed as the average rain fallen at the weather stations over the entire region of interest during four consecutive days, including rain that occurred on weekends. For day i, the rain variable is

$$Rain_i^{Region} \equiv \frac{1}{4}\frac{1}{Nstations}(\sum_{j=1}^{4}\sum_{k=1}^{Nstations} R_{i+j}^{stationk}), \tag{18}$$

where $Nstations$ is the number of stations in the region of interest. For every summer in each period I record the daily price change and daily rain precipitation variable in every trading day between the beginning of January and the end of February, and estimate the theoretical return (16) for Argentina through the econometric specification [4]

$$\frac{P_i^{May} - P_{i-1}^{May}}{P_{i-1}^{May}} = \beta^{Argentina} Rain_i^{Argentina} + Controls_i + Const + \epsilon_i. \tag{19}$$

The CME price P^{May} corresponds to the contract expiring on the forthcoming May, at the end of the current growing season as seen from day i. I estimate (16) for the US Midwest using the approach outlined above but using US Midwest rain precipitation data and daily price changes recorded from the beginning of July to the end of August,

$$\frac{P_i^{Nov} - P_{i-1}^{Nov}}{P_{i-1}^{Nov}} = \beta^{Midwest} Rain_i^{Midwest} + Controls_i + Const + \epsilon_i. \tag{20}$$

The price variable P^{Nov} corresponds to the CME contract with expiration at the end of the current growing season as seen from day i. The separate regressions that I run for Argentina and the US are symmetric in the fact that I use price changes for futures delivery dates at the end of the respective growing seasons.

The simple model introduced in Section 3 that led to (16) explains price changes by the supply effect caused by rain, and random rain forecasting errors. According to Tannura

[4]Regressions for (19) and (20) are run on daily rain, daily price changes and daily control changes. I verified that all these variables are stationary in the sample under consideration.

et al. (2008), soybean output is also negatively affected by high summer temperatures. I control by the effect of temperature on prices by adding an explanatory variable defined, for day i, as

$$Temp_i^{Region} \equiv \frac{1}{4}\frac{1}{Nstations}(\sum_{j=1}^{4}\sum_{k=1}^{Nstations} Temp_{i+j}^{stationk}), \tag{21}$$

where $Temp_j^{stationk}$ is the maximum temperature recorded on day j at weather station k after filtering the seasonal component. Therefore, the spatial and temporal averaging in $Temp_i^{Region}$ is identical to that in the construction of $Rain_i^{Region}$.

Price changes are also caused by a myriad of other factors, discussed for example by Frankel and Rose (2009). The overall level of commodity prices has been found to be strongly influenced by the level of global economic activity and, in recent years, increased financial speculation. I take into account these these effects by including daily percentage changes in the price of West Texas Intermediate Oil, in US dollars per barrel, as a control. Commodity prices, denominated in US dollars, are potentially sensitive to the strength of this currency. I control for this effect by including daily percentage changes on an equally weighted basket of exchange rates between the US dollar vs. the Euro and the Chinese Yuan, which represent some of the most important economic regions involved in soybean international trade. Finally, the potential effect of varying transportation costs in the price of soybeans is taken into account by adding daily percentage changes in the Baltic Dry Index as a control. This is a widely followed indicator of the cost of bulk freight shipping along several maritime routes used in international trade.

I first consider a decomposition of the data set in two long periods. For Argentina, the first period includes every day in the midsummers from 1997 to 2003, ending in February 2003, and the second period includes the midsummers from 2004 to 2010. The US Midwest first period includes the (northern hemisphere) midsummers, starting in July and ending in August, from 1996 to 2002. Midsummers from 2003 to 2010 belong in the second period. The data available from the beginning of 1996 up to the time of writing this paper includes fourteen summers for Argentina and fifteen summers for the US. The discrepancy between periods across regions is minimal given the fact that summers in these regions are six months apart. Soybean production from Latin America, including Argentina and Brazil, surpassed US output in 2003, therefore this event coincides roughly with the break between the two periods I consider.

I also estimate model (16) for each region partitioning the data set in biennial periods. The estimates of β^{US} and β^{Arg} in (19) and (20) for biennial periods between 1996 and 2010 are then used to test the second prediction of model (16), namely the existence of a linear relationship between price impact of rain and regional market shares for physically similar regions. This is a second regression

$$\beta^{Region}_{Period} = \delta S^{Region}_{Period} + Const + \epsilon^{Region}_{Period}, \tag{22}$$

where S^{Region}_{Period} is the average market share of the central region of Argentina or the US Midwest over each biennial period.

5. The Data

5.1. *Price data*

I obtained daily CME price data from Bloomberg for the period May 1st, 1996 to October 29th, 2010. Soybean future prices are available every trading day for contract expirations in January, March, May, July, August, September and November. Underlying in a soybean future contract are 5000 bushels (approximately equal to 136.091 metric tons) of soybean of certain quality. The last trading day is the business day prior to the 15th calendar day of the contract month. The price is expressed as US dollar cents per bushel. In Figure 3 I display historical futures prices, for the nearest delivery date, for soybeans and soybean meal. Prices are converted to US dollars per metric ton.

5.2. Rain and temperature data

Rain precipitation and average temperature data, both with daily frequency between January 1st, 1996 and December 31st, 2010, were obtained from the National Climatic Data Center (NCDC) administered by the National Oceanic and Atmosphere Administration (NOAA). Rain data is reported as inches of rain fallen within a 24 hour period. Average daily temperature is expressed in degrees Fahrenheit. Data is available for over 9000 stations distributed worldwide. Recordings are made in each country by a local meteorological governmental institution and exchanged with NOAA under the World Meteorological Organization (WMO) Weather Watch Program. I identified a list of representative weather stations in the core soybean planting region in Argentina and in the US Midwest. Data in Argentina was collected for Aeroparque (City of Buenos Aires), Ceres, Cordoba, Junin, Parana, Rio Cuarto, Rosario and Tandil. These weather stations are within, or adjacent to, the provinces of Buenos Aires, Cordoba, Entre Rios, and Santa Fe, that form the main soybean producing region in Argentina. Data for the US Midwest was collected for Greater Peoria (IL), Springfield (IL), Scott AFB (IL), Des Moines (IA), Waterloo (IA), Sioux City (IA), Omaha (NE), Lincoln (NE), Toledo (OH), Columbus (OH), Kansas (MO), Whiteman (MO), St. Cloud (MN), Rochester (MN), Purdue (IN), Grissom (IN) and South Bend (IN). Tables V and VI display statistics for average midsummer temperature and total midsummer rain at weather stations in Argentina and the US Midwest respectively. In rare occasions (less than 3% and 1.6% for rain data in Argentina and the US respectively, even less often for temperature), a weather variable for a specific date and station is missing. In this case, the spatial average (18) is computed over the reduced number of weather stations. Unreported regressions treating the missing rain observations as zeros lead to results that are very similar to those reported in this paper.

5.3. Controls

All controls have daily frequency. The spot price for West Texas Intermediate oil, in US dollars per barrel, was obtained from the US Energy Information Administration (EIA) and denoted as Oil. The second control, denoted as FXRate was constructed using the nominal exchange rates between the Euro and the US dollar and between the Chinese Yuan and the US dollar obtained from the database in the Pacific Exchange Rate Service at the Sauder School of Business of the University of British Columbia. The third control is the Baltic Dry Index, denoted by BDI, and available from Bloomberg.

5.4. Production data

Global and regional soybean production and export data was collected from the USDA *Oilseeds Report* for December 2006, December 2010, and May 2011 [5], the USDA *Agricultural Statistics Report* for 1997, 2000, 2003, 2006, 2009, and 2011 [6], and from the online Agricultural Information Database of Argentina's Ministry of Agriculture, Livestock, and Fisheries [7]. Production statistics, including regional yields, are presented in Tables I, II and III in Section 2.

5.5. Irrigation data

Irrigation data was collected from the US Geological Survey (Hutson et al. (2004)). Irrigated Area by State is reported in Table IV in Section 2.

[5] http://www.fas.usda.gov/oilseeds_arc.asp.
[6] http://www.nass.usda.gov/Publications/Ag_Statistics/
[7] http://www.siia.gov.ar/index.php/series-por-tema/agricultura

6. Results and Analysis

6.1. Rain and output

As anticipated in Section 4, I begin by verifying empirically that regional rain has a positive impact on regional yield. Estimation results of (17) are reported in Table VII. The regressions show that the separate impacts of midsummer and extended summer rain on annual yield are statistically significant and positive for both regions. In addition, the hypothesis that both regions have equal sensitivity to local rain can not be rejected for the midsummer or extended summer periods. It is in this sense that I state, in the remainder of the paper, that the US Midwest and the central region of Argentina are biologically similar in their response to local rain. Results in Table VII also show that, in both regions, yields are more sensitive to rain during the midsummer than during the extended summer.

6.2. Midsummer rain on prices

I estimate (19) and (20) by OLS regressions with heteroscedasticity and autocorrelation robust Newey-West standard errors. Results in Table VIII show that midsummer rain in Argentina during the period 1997-2003 had no significant impact on CME prices, and rain during the period 2004-2010 led, in average, to a 1.6% CME price decrease per inch of rain, significant at the 1% level. This is consistent with the notion that additional rain leads to a price decrease through an increase in expected output. Rain impact in the US Midwest implied a 5.1% price fall during the first period, significant at the 1% level, and a 1.8% price fall during the second period, significant at the 10% level. The Oil price explanatory variable had a positive and strongly significant coefficient in the second period, for both regions, reflecting increasing correlation across commodities. This is consistent with the results documented by Tang and Xiong (2009). The FX Rate and the Baltic Dry Index did not have a consistent contribution to the explanation of CME price changes. Surprisingly, daily temperatures departures from their periodical seasonal variation had no statistically significant effect on CME price changes. In addition, unreported experiments using the average temperature over the next ten (rather than four) days, or using first order time differences in future temperature, also failed to find a discernible impact of these variables on CME price fluctuations. The muted response of prices to temperature might perhaps be due to the fact that total midsummer rain seems more volatile than average midsummer temperature, as suggested by the ratio of their corresponding means and standard deviations in Tables V and VI.

In order to understand the economic significance of the estimated rain impact is useful to recall, from Tables V and VI, that historical average rain precipitation has been close to 10 inches for the midsummer in any of these two regions. Therefore, one inch of rain is biologically important and this precipitation leads to an economically significant price decrease in any of the two regions in the second period.

6.3. Extended summer rain on prices

I evaluate the sensitivity of the results in Table VIII to the choice of summer months by estimating (19) and (20) using every month in the extended summer season rather than midsummer months. Table IX shows rain's impact on the CME price for the central region of Argentina and the US Midwest. For the period 1997-2003 the impact of rain in Argentina was not significant, and that for the period 2004-2010 the impact of rain was significant at the 5% level and implied a 0.7% fall in the CME price per inch of rain in the central region of Argentina. Results for the US Midwest in Table IX show that for the period 1996-2002 the impact of rain in the US Midwest was significant at the 1% level and implied a 1.9% fall in the CME price per inch of rain in the US Midwest. This effect decreased in importance in the period 2003-2010, when the rain sensitivity in the

US Midwest implied a 0.9% fall in the CME price per inch of local rain, significant at the 5% level. Oil and FXRate were strongly significant in the second period, with the expected positive and negative sign respectively.

A comparison between Tables VIII and IX shows that the effect of an inch of rain on CME prices during midsummer months is much stronger than the effect during the extended summer months. This is consistent with the results reported earlier in Table VII, also documented by Tannura et al. (2008), which show that output is most sensitive to midsummer rain. The response of CME prices to rain during these months suggests that market participants are aware of this biological feature.

6.4. Recent rain and temperature on prices

I also estimate (19) and (20) using recent rain or seasonally adjusted recent temperature. They are defined as the average weather quantity over the three days from $i-3$ to $i-1$ for the price change between $i-1$ and i. Results for the midsummer in each region, reported in Table X, show no significant effects for recent rain or temperature. This suggests that CME market participants have already incorporated into prices the information related to the occurrence of recent weather events, consistent with the anticipation of rain events evidenced in the results presented in Tables VIII and IX.

6.5. Rain's price impact and market share

The preceding empirical results show, through the statistical and economic significance of the OLS rain coefficients in Tables VIII and IX, that the CME market incorporates information about supply shocks caused by rain in the spatially and temporally distributed production of soybeans. Prices respond, during the midsummer or extended summer months, to rain on soybean producing regions on near future days, consistently with available weather forecasting technology. Prices do not respond to recent rain which, I interpret, has already been incorporated into prices.

A main goal of this paper is to understand the importance of the distributed nature of production. To this end, I analyze to what extent the price impact of rain in a specific region is related to its global market share. Multiplying the ratios representing the share of global output produced by Argentina reported in Table I, and the share of national output produced by the central region of Argentina reported in Table II, I find that the central region of Argentina produced an average of 12.3% of global output between 1997 and 2003 and 16.5% of global output between 2004 and 2010. This output growth coincides in time with the increased impact of Argentina's rain on CME prices documented in Tables VIII and IX. Identical computation, using the information in Tables I and III implies global market shares for the US Midwest of 30.8% and 23.6% for the first and second periods respectively. Not surprisingly, Tables I and III show a decreased sensitivity of CME prices to US rain in the second period.

I test for the existence of a relationship between market share and price impact by estimating (22). In order to generate a sufficiently large number of rain impact measurements across time I repeat the estimation of (19) and (20) breaking the dataset on biennial periods (except for the summer of 1996 in the US, which is a period in itself), hence generating 15 point estimates of the impact of rain on daily price changes. These are reported in Table XI. Although noisier than those reported in Tables VIII and IX, all significant estimates in Table XI have negative sign as expected.

Market shares over biennial periods are computed in the manner described above and, together with biennial rain impacts, are reported in the first two columns of Table XII. This information is also displayed in Figure 4, which makes apparent a linear relationship between market share and rain's impact on the CME price. The statistical significance of this finding is reported in Table XII. The slope coefficient is significant at the 1% level, and R^2 is in excess of 0.77. This is evidence of a strong empirical linear relationship between market share and local rain impact on the CME price. Such linear relationship is consistent with the prediction of the very simple model of Section 3 for regions that are biologically similar in their response to rain. Remarkably, CME traders seem to aggregate supply shocks linearly, regardless of their geographical origin.

An alternative to testing the model in Section 3 under the restriction $\gamma^{Argentina} = \gamma^{Midwest}$ as above, is to consider the unrestricted case in which regions are allowed to be different in their output response to rain. In this case, the model in Section 3 predicts, through (16), that regional market share should be proportional to the price impact of rain β^{Region} divided by γ^{Region}. In turn, a comparison of (5) and (17), shows that α^{Region} in Table VII is an estimate of $\gamma^{Region}\bar{Y}^{Region}$. Therefore, in the unrestricted case, the model in Section 3 predicts that regional market share should be proportional to the ratio $(\beta^{Region}\bar{Y}^{Region})/\alpha^{Region}$. Such renormalized rain impact coefficient is presented in the last column of Table XII, together with the results of a linear regression of the form (22) using the renormalized rain impact as dependent variable. Results in Table XII show strong support for the predicted linear relationship. Therefore, the empirical evidence is consistent with a model in which CME traders aggregate global supply in a linear fashion, but can not distinguish if traders assume the regions are equal in their biological response to rain, or slightly different as suggested by the estimates in Table VII.

Results in Table XII also indicate the existence of a positive constant term, which would be unexplained by the simple additive model of Section 3 in which an additional unit of supply anywhere in the world has the same impact on the CME price. Market shares are nonnegative, and statistically significant rain impact coefficients are negative. Therefore, a positive constant term would imply that a region should achieve a certain minimum market share before having an impact on the CME market. The size of this constant term is about a tenth of the magnitude of the slope coefficient that can be interpreted as the rain impact for a region with 100% market share. It is in this sense that the estimated linear relationship is close to the prediction of the model in Section 3.

A final caveat applies. If rain precipitation in the soybean producing regions in Brazil, which is not considered explicitly in this paper due to the lack of good quality data, is in reality positively correlated with rain in Argentina, then the interpretation of the results outlined above should be modified accordingly. In this case, the effective market share that should be associated with rain in Argentina should include some fraction of the output grown in Brazil. Therefore, the estimate of the slope in the regression of Table XII would likely become even more negative, and the estimate of the constant term even more positive.

In summary, the empirical evidence presented in this Section is generally consistent with the predictions of the model in Section 3: the price impact of local rain, across periods and regions, is generally negative, and statistically and economically significant. The magnitude of the impact of rain on the CME price is close to linearly related to regional shares of global production, although there is evidence of a small positive constant term in the relationship between regional market share and price impact of rain. This is roughly consistent with the CME being the reflection of a globally integrated market for soybeans that aggregates supply shocks in a linear fashion and that is, to a large extent, indifferent about the geographical origin of supply.

7. Conclusions

I study in this paper how exogenous local supply shocks in the distributed production of soybeans were incorporated into CME prices. Shocks were caused by rain precipitation in the central region of Argentina and the US Midwest, which combined account for close to 45% of global production. I generally find that rain precipitation had an economically important negative price impact, consistent with the fact that rain increases output and this increase in supply should lead to a decrease in prices. I also find that the price impact of rain, across regions and periods, is close to linearly related with with the share of global output produced locally. This is generally consistent with the prediction of a very simple model that postulates a globally integrated market for soybeans in which an additional unit of supply anywhere in the world has the same impact in the CME price. US based risk managers are therefore increasingly exposed to shocks outside of the US.

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	World Prod.	US Prod.	US Share	US Yield	Arg. Prod.	Arg. Share	Arg. Yield
96/97	132.3	64.78	0.49	2.53	11.20	0.08	1.81
97/98	158.24	73.18	0.46	2.62	19.50	0.12	2.80
98/99	159.83	74.60	0.47	2.62	20.00	0.13	2.45
99/00	160.35	72.22	0.45	2.46	21.20	0.13	2.47
00/01	175.76	75.06	0.43	2.56	27.80	0.16	2.67
01/02	184.82	78.67	0.43	2.66	30.00	0.16	2.63
02/03	196.87	75.01	0.38	2.56	35.50	0.18	2.82
03/04	186.64	66.78	0.36	2.28	33.00	0.18	2.36
04/05	215.78	85.02	0.39	2.84	39.00	0.18	2.71
05/06	220.67	83.51	0.38	2.90	40.50	0.18	2.66
06/07	236.23	87.00	0.37	2.88	48.80	0.21	2.99
07/08	220.47	72.86	0.33	2.81	46.20	0.21	2.82
08/09	211.96	80.75	0.38	2.67	32.00	0.15	2.00
09/10	260.84	91.42	0.35	2.96	54.50	0.21	2.93
10/11	261.97	90.61	0.35	2.92	49.50	0.19	2.66
Mean	198.85	78.09	0.40	2.68	33.91	0.16	2.45

Table I: Soybean annual production, in millions of metric tons, for the World, US, and Argentina, corresponding global market shares, and yields (in tons per hectare). Data was obtained from the USDA *Oilseeds Report* for December 2006, December 2010, and May 2011. 96/97 refers to the October 1996 harvest for the US, and the April 1997 harvest for Argentina.

Year	Bs. As.	Cdba.	E. Rios	Sta. Fe	Argentina	Share Central	Yield Central
96/97	2.53	2.91	0.28	4.16	11.00	0.90	1.69
97/98	3.86	5.82	0.73	7.31	18.73	0.95	2.76
98/99	4.58	5.26	0.76	7.30	19.96	0.90	2.49
99/00	3.78	6.93	0.54	6.64	20.12	0.89	2.36
00/01	5.73	8.15	1.66	8.66	26.87	0.90	2.68
01/02	5.78	9.66	1.91	8.35	29.96	0.86	2.70
02/03	7.14	9.85	2.81	10.22	34.78	0.86	2.92
03/04	7.85	8.38	2.31	9.14	31.51	0.88	2.34
04/05	10.00	11.19	3.05	10.45	38.22	0.91	2.93
05/06	10.53	11.12	2.80	10.28	40.47	0.86	2.74
06/03	11.65	14.17	3.93	11.30	47.38	0.87	3.10
07/08	12.25	12.75	3.29	11.48	46.16	0.86	2.95
08/09	6.74	11.17	1.14	8.08	30.94	0.88	1.99
09/10	17.05	12.99	4.03	10.43	52.61	0.85	2.96
Mean	7.82	9.31	2.09	8.14	32.05	0.88	2.62

Table II: Soybean annual production, in millions of metric tons, for the four provinces in the central region of Argentina. Also reported: total national output, share of national output produced by the central region of Argentina, and corresponding yield (tons per hectare). Data was obtained from the Agricultural Information Data Center of Argentina's Ministry of Agriculture, Livestock and Fisheries. http://www.siia.gov.ar/index.php/series-por-tema/agricultura.

Year	IL	IN	IA	MN	MO	NE	OH	US	Share Midwest	Yield Midwest
96/97	10.86	5.54	11.32	6.10	4.08	3.69	4.28	64.84	0.71	2.69
97/98	11.65	6.28	13.02	6.95	4.75	3.91	5.20	73.18	0.71	2.85
98/99	12.63	6.29	13.52	7.77	4.63	4.49	5.26	74.61	0.73	2.91
99/00	12.06	5.89	13.02	7.70	4.00	4.92	4.41	71.94	0.72	2.69
00/01	12.51	6.86	12.65	7.98	4.76	4.73	5.08	75.06	0.73	2.82
01/02	13.01	7.46	13.08	7.25	5.07	6.07	5.11	78.68	0.72	2.89
02/03	12.24	6.42	13.47	8.41	4.63	4.80	3.85	74.30	0.72	2.78
03/04	10.33	5.55	9.33	6.49	3.97	4.96	4.49	66.78	0.68	2.35
04/05	13.47	7.74	13.54	6.33	6.08	5.95	5.65	85.02	0.69	3.11
05/06	12.09	7.18	14.50	8.33	5.00	6.41	5.49	84.01	0.70	3.18
06/07	13.13	7.73	13.88	8.78	5.29	6.82	5.91	87.01	0.71	3.18
07/08	9.80	6.00	12.21	7.28	4.77	5.34	5.42	72.87	0.70	3.08
08/09	11.64	6.65	12.11	7.19	5.20	6.15	4.39	80.54	0.66	2.90
09/10	11.71	7.26	13.23	7.75	6.28	7.06	6.04	91.43	0.65	3.18
10/11	12.69	7.04	13.51	8.95	5.73	7.29	6.00	90.62	0.68	3.27
Mean	11.99	6.66	12.83	7.55	4.95	5.51	5.10	78.06	0.70	2.93

Table III: Soybean annual production, in millions of metric tons, for states in the US Midwest, defined as the combined output of IL, IN, IA, MN, MO, NE and OH. Also reported: total national output, share of national output produced by the US Midwest, and corresponding yield (tons per hectare). Data is taken from the USDA *Agricultural Statistics Report* for 1997, 2000, 2003, 2006, 2009, and 2011.

State	Irrigated Land	State Area	Ratio
Illinois	569.4	57,914	0.010
Indiana	390.0	36,418	0.011
Iowa	131.8	56,272	0.002
Minnesota	893.9	86,939	0.010
Missouri	2,074.8	69,704	0.030
Nebraska	11,575.2	77,354	0.150
Ohio	95.2	44,825	0.002

Table IV: Irrigated area and state area in square miles, and their ratio. Data was obtained from *Estimated Use of Water in the United States in 2000* by the US Geological Survey (Hutson et al.(2004)).

Total midsummer rain				
	Avg 97-03	Std dev 97-03	Avg 04-10	Std dev 04-10
Aeroparque	6.68	4.81	9.76	4.39
Ceres	10.07	7.01	7.96	3.20
Cordoba	9.42	3.66	9.03	3.88
Junin	8.18	4.12	10.59	4.76
Parana	7.79	3.72	9.75	5.62
Rio Cuarto	6.61	4.73	15.56	6.75
Rosario	7.84	3.20	10.27	7.50
Tandil	7.21	4.21	7.55	6.94
Average midsummer temperature				
	Avg 97-03	Std dev 97-03	Avg 04-10	Std dev 97-03
Aeroparque	74.7	2.1	75.5	0.7
Ceres	75.9	1.6	77.8	1.1
Cordoba	72.4	1.7	73.2	1.2
Junin	71.5	2.5	72.4	0.6
Parana	75.3	1.9	76.4	1.2
Rio Cuarto	72.3	2.0	72.3	1.0
Rosario	75.5	2.2	75.3	1.3
Tandil	67.7	2.1	68.0	2.2

Table V: Summary statistics for total midsummer rain and average midsummer temperature at weather stations in central Argentina. Rain measured in inches, temperature in degrees Fahrenheit. Data from the National Climatic Data Center administered by the National Oceanic and Atmosphere Administration.

Total midsummer rain				
	Avg 96-02	Std dev 96-02	Avg 03-10	Std dev 03-10
Greater Peoria IL	6.00	1.43	6.60	1.63
Springfield IL	6.59	1.51	6.55	2.35
Scott AFB IL	7.35	2.21	7.62	3.45
Des Moines IW	6.84	2.23	9.00	3.70
Waterloo IW	8.32	4.39	9.05	4.21
Sioux City IW	6.91	3.35	7.59	2.65
Omaha NE	8.27	4.66	8.15	3.05
Lincoln NE	6.85	2.38	5.72	1.88
Toledo OH	4.66	1.93	8.10	2.41
Columbus OH	7.03	1.63	8.67	2.30
Kansas MO	5.17	2.57	8.25	3.72
Whiteman MO	7.92	4.75	8.48	5.20
St Cloud MN	6.70	2.34	6.29	1.87
Rochester MN	9.21	3.01	8.34	3.53
Purdue IN	5.69	2.25	7.32	2.00
Grissom IN	7.34	2.86	9.57	4.83
South Bend IN	6.46	1.61	8.79	4.07
Average midsummer temperature				
	Avg 96-02	Std dev 96-02	Avg 03-10	Std dev 03-10
Greater Peoria IL	74.7	1.5	74.4	2.7
Springfield IL	74.8	1.1	74.5	2.7
Scott AFB IL	77.6	1.1	76.6	2.5
Des Moines IW	74.7	1.4	75.0	2.7
Waterloo IW	72.3	1.2	71.7	2.4
Sioux City IW	73.3	1.4	73.8	2.3
Omaha NE	75.9	1.5	75.8	2.7
Lincoln NE	76.7	1.8	76.6	2.3
Toledo OH	72.2	2.2	72.3	1.9
Columbus OH	74.4	1.9	74.4	1.9
Kansas MO	77.6	1.8	77.8	3.0
Whiteman MO	79.7	2.5	76.3	2.9
St Cloud MN	69.4	1.6	69.7	2.6
Rochester MN	69.1	1.5	69.5	2.6
Purdue IN	73.8	1.2	73.3	2.2
Grissom IN	73.3	3.7	74.0	2.5
South Bend IN	72.1	2.1	71.9	2.2

Table VI: Summary statistics for total midsummer rain and average midsummer temperature at weather stations in the US Midwest. Rain measured in inches, temperature in degrees Fahrenheit. Data from the National Climatic Data Center administered by the National Oceanic and Atmosphere Administration.

	Annual yield US Midwest	Annual yield Central Argentina
Midsummer rain	0.161***	0.117***
	(0.048)	(0.043)
Const	1.730***	1.508***
	(0.357)	(0.421)
R^2	0.467	0.402

	Annual yield US Midwest	Annual yield Central Argentina
Extended summer rain	0.030*	0.042**
	(0.020)	(0.017)
Const	2.268***	1.447***
	(0.445)	(0.492)
R^2	0.146	0.350

Table VII: Impact of midsummer (top panel) and extended summer (bottom panel) rain on regional yield. Estimation results by OLS regressions of $Y_i^{Region} = \alpha^{Region} R_i^{Region} + Const + \epsilon_i$. Yields, midsummer and extended summer rain, with annual frequency, 1996/7-2010. By *, ** and *** I indicate statistical significance at the 10%, 5% and 1% levels.

Estimation results by OLS regression with Newey-West standard errors, including five lags, of

$$\frac{P_i^{May} - P_{i-1}^{May}}{P_{i-1}^{May}} = \alpha + \beta_0 Rain_i^{Arg} + \beta_1 Oil_i + \beta_2 FXRate_i + \beta_3 BDI_i + \beta_4 Temp_i^{Arg} + \epsilon_i,$$

for the effect of rain precipitation and controls on the daily percentage change in CME May Soybean future price. All controls are percentage changes between day $i-1$ and day i. The variable Rain at day i is the average rain recorded on 8 weather stations in the central region of Argentina over the four consecutive days starting on day $i+1$. Sample: Monday to Friday, from the first day in January to the last day in February, for every year between 1997 to 2010. Rain data includes weekend recordings. I also report results from the estimation of

$$\frac{P_i^{Nov} - P_{i-1}^{Nov}}{P_{i-1}^{Nov}} = \alpha + \beta_0 Rain_i^{US} + \beta_1 Oil_i + \beta_2 FXRate_i + \beta_3 BDI_i + \beta_4 Temp_i^{US} + \epsilon_i,$$

for the effect of rain precipitation and controls on the daily percentage change in CME November Soybean future price. All controls are percentage changes between day $i-1$ and day i. The variable Rain at day i is the average daily rain recorded on 17 weather stations in the the US Midwest over the four consecutive days starting on day $i+1$. Sample: Monday to Friday, from the first day in July to the last day in August, for every year between 1996 to 2010. Rain data includes weekend recordings. By *, ** and *** I indicate statistical significance at the 10%, 5% and 1% levels.

	Argentina 97 - 03	Argentina 04 - 10	US 96 - 02	US 03 - 10
Rain	0.0029	-0.0156^{***}	-0.0513^{***}	-0.0183^{*}
	(0.0038)	(0.0045)	(0.0112)	(0.0094)
Oil	-0.0015	0.1655^{***}	-0.0284	0.2624^{***}
	(0.0256)	(0.0406)	(0.0423)	(0.0563)
FXRate	0.2160	-0.6343^{**}	-0.2445	-0.3746
	(0.2186)	(0.2827)	(0.2898)	(0.2974)
BDI	-0.0111	0.0718^{**}	-0.0511	-0.0639
	(0.0535)	(0.0313)	(0.1806)	(0.0519)
Temperature	-0.0002	-0.0003	0.0000	0.0002
	(0.0002)	(0.0003)	(0.0003)	(0.0002)
Const	-0.0007	0.0037^{***}	0.0059^{***}	0.0018
	(0.0009)	(0.0013)	(0.0015)	(0.0016)
Observations	297	295	311	353
R-squared	0.0100	0.1434	0.0525	0.0961

Table VIII: Impact of midsummer rain in Argentina and US Midwest on CME Soybean future prices.

Estimation results by OLS regression with Newey-West standard errors, including five lags, of

$$\frac{P_i^{May} - P_{i-1}^{May}}{P_{i-1}^{May}} = \alpha + \beta_0 Rain_i^{Arg} + \beta_1 Oil_i + \beta_2 FXRate_i + \beta_3 BDI_i + \beta_4 Temp_i^{Arg} + \epsilon_i,$$

for the effect of rain precipitation and controls on the daily percentage change in CME May Soybean future price. All controls are percentage changes between day $i-1$ and day i. The variable Rain at day i is the average rain recorded on 8 weather stations in the central region of Argentina over the four consecutive days starting on day $i+1$. Sample: Monday to Friday, from the first day in November, to the last day in April of the following year, for 1996 to 2009. Rain data includes weekend recordings. I also report results, using the same methodology, of the estimation of

$$\frac{P_i^{Nov} - P_{i-1}^{Nov}}{P_{i-1}^{Nov}} = \alpha + \beta_0 Rain_i^{US} + \beta_1 Oil_i + \beta_2 FXRate_i + \beta_3 BDI_i + \beta_4 Temp_i^{US} + \epsilon_i,$$

for the effect of rain precipitation and controls on the daily percentage change in CME November Soybean future price. All controls are percentage changes between day $i-1$ and day i. The variable Rain at day i is the average daily rain recorded on 17 weather stations in the the US Midwest over the four consecutive days starting on day $i+1$. Sample: Monday to Friday, from the first day in May, to the last day in October, for 1996 to 2010. Rain data includes weekend recordings. By *, ** and *** I indicate statistical significance at the 10%, 5% and 1% levels.

	Argentina 97 - 03	Argentina 04 - 10	US 96 - 02	US 03 - 10
Rain	-0.0014	-0.0065^{**}	-0.0187^{***}	-0.0094^{**}
	(0.0023)	(0.0031)	(0.0061)	(0.0046)
Oil	0.0180	0.1652^{***}	0.0016	0.2763^{***}
	(0.0109)	(0.0229)	(0.0179)	(0.0271)
FXRate	0.0611	-0.8015^{***}	-0.1613	-0.6520^{***}
	(0.1219)	(0.1569)	(0.1373)	(0.1970)
BDI	0.0202	0.0171	-0.0473	-0.0060
	(0.0395)	(0.0287)	(0.0697)	(0.0256)
Temperature	-0.0001	-0.0001	0.0001	0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Const	0.0003	0.0019^{***}	0.0019^{**}	0.0013
	(0.0005)	(0.0007)	(0.0009)	(0.0008)
Observations	905	907	921	1050
R-squared	0.0038	0.1413	0.0148	0.1662

Table IX: Impact of extended summer rain in Argentina and US Midwest on CME Soybean future prices.

Estimation results by OLS regression with Newey-West standard errors, including five lags, of

$$\frac{P_i^{May} - P_{i-1}^{May}}{P_{i-1}^{May}} = \alpha + \beta_0 Rain_i^{Arg} + \beta_1 Oil_i + \beta_2 FXRate_i + \beta_3 BDI_i + \beta_4 Temp_i^{Arg} + \epsilon_i,$$

for the effect of rain precipitation and controls on the daily percentage change in CME May Soybean future price. All controls are percentage changes between day $i-1$ and day i. The variable Rain at day i is the average rain recorded on 8 weather stations in the central region of Argentina from day $i-3$ to day $i-1$. Sample: Monday to Friday, from the first day in January to the last day in February, for every year between 1997 and 2010. Rain data includes weekend recordings. I also report results, using the same methodology, of the estimation of

$$\frac{P_i^{Nov} - P_{i-1}^{Nov}}{P_{i-1}^{Nov}} = \alpha + \beta_0 Rain_i^{US} + \beta_1 Oil_i + \beta_2 FXRate_i + \beta_3 BDI_i + \beta_4 Temp_i^{US} + \epsilon_i,$$

for the effect of rain precipitation and controls on the daily percentage change in CME November Soybean future price. All controls are percentage changes between day $i-1$ and day i. The variable Rain at day i is the average daily rain recorded on 17 weather stations in the the US Midwest from day $i-3$ to day $i-1$. Sample: Monday to Friday, from the first day in July to the last day in August, for every year between 1996 to 2010. Rain data includes weekend recordings. By *, ** and *** I indicate statistical significance at the 10%, 5% and 1% levels.

	Argentina 97 - 03	Argentina 04 - 10	US 96 - 02	US 03 - 10
Rain	0.0047	-0.0029	-0.0142	0.0029
	(0.0036)	(0.0040)	(0.0101)	(0.0089)
Oil	0.0003	0.1597***	-0.0230	0.2656***
	(0.0260)	(0.0406)	(0.0424)	(0.0572)
FXRate	0.2234	−0.6406**	-0.1199	-0.3953
	(0.2151)	(0.2842)	(0.3146)	(0.2964)
BDI	-0.0072	0.0702**	-0.0879	-0.0649
	(0.0545)	(0.0331)	(0.1894)	(0.0515)
Temperature	-0.0001	-0.0004	0.0003	0.0001
	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Const	-0.0009	0.0015	0.0022	-0.0010
	(0.0008)	(0.0012)	(0.0016)	(0.0016)
Observations	297	295	311	353
R-squared	0.0105	0.1217	0.0106	0.0880

Table X: Impact of recent rain in Argentina and US Midwest on CME Soybean future price.

Estimation results by OLS regression with Newey-West standard errors, including three lags, of

$$\frac{P_i^{May} - P_{i-1}^{May}}{P_{i-1}^{May}} = \alpha + \beta_0 Rain_i^{Arg} + \beta_1 Oil_i + \beta_2 FXRate_i + \beta_3 BDI_i + \beta_4 Temp_i^{Arg} + \epsilon_i,$$

for the effect of rain precipitation and controls on the daily percentage change in CME May Soybean future price. All controls are percentage changes between day $i-1$ and day i. The variable Rain at day i is the average rain recorded on 8 weather stations in the central region of Argentina from day $i-3$ to day $i-1$. Sample: Monday to Friday, from the first day in January to the last day in February for every year between 1997 to 2010. Rain data includes weekend recordings. I also report results, using the same methodology, of the estimation of

$$\frac{P_i^{Nov} - P_{i-1}^{Nov}}{P_{i-1}^{Nov}} = \alpha + \beta_0 Rain_i^{US} + \beta_1 Oil_i + \beta_2 FXRate_i + \beta_3 BDI_i + \beta_4 Temp_i^{US} + \epsilon_i,$$

for the effect of rain precipitation and controls on the daily percentage change in CME November Soybean future price. All controls are percentage changes between day $i-1$ and day i. The variable Rain at day i is the average daily rain recorded on 17 weather stations in the the US Midwest from day $i-3$ to day $i-1$. Sample: Monday to Friday, from the first day in July to the last day in August for every year between 1996 to 2010. Rain data includes weekend recordings. By *, ** and *** I indicate statistical significance at the 10%, 5% and 1% levels. In the interest of space I only report estimates of the impact of rain.

Region and Period	Rain (β_0)	Std. Error	N observations	R-squared
Arg 97-98	0.0092	0.0081	85	0.015
Arg 99-00	0.0163	0.0123	83	0.057
Arg 01-02	-0.0012	0.0049	86	0.109
Arg 03-04	-0.0143	0.0116	85	0.054
Arg 05-06	-0.0213^{***}	0.0060	83	0.260
Arg 07-08	-0.0126	0.0129	87	0.242
Arg 09-10	-0.0041	0.0075	83	0.137
US 96	-0.0515^{***}	0.0170	45	0.233
US 97-98	-0.0416^{*}	0.0219	88	0.086
US 99-00	-0.0596^{*}	0.0348	88	0.054
US 01-02	-0.0439^{*}	0.0227	90	0.086
US 03-04	-0.0215	0.0164	88	0.042
US 05-06	-0.0060	0.0159	88	0.049
US 07-08	-0.0301	0.0276	89	0.273
US 09-10	-0.0314^{*}	0.0170	88	0.229

Table XI: Impact of midsummer rain in Argentina and US Midwest on CME Soybean future price, over biennial periods.

Estimation results by OLS regression with Newey-West standard errors of

$$\beta_{Period}^{Region} = \delta S_{Period}^{Region} + Const + \epsilon_{Period}^{Region}.$$

The dependent variable is the impact of rain, defined as the OLS coefficient of the CME soybean price change on daily rain, in a certain period and region, or its renormalized form. Values are taken from Table XI and reproduced below. The explanatory variable is the average share of global production for certain region and period, computed using data from Tables I, II and III. The upper part of the table below presents the data, and the bottom part presents the results of the regression. By *, ** and *** I indicate statistical significance at the 10%, 5% and 1% levels.

Region and period	Share global prod.	Rain impact	Normalized Rain impact
Central Argentina 97-98	0.093	0.0092	0.2056
Central Argentina 99-00	0.116	0.0163	0.3660
Central Argentina 01-02	0.141	−0.0012	−0.0271
Central Argentina 03-04	0.157	−0.0143	−0.3208
Central Argentina 05-06	0.159	−0.0213	−0.4766
Central Argentina 07-08	0.182	−0.0126	−0.2816
Central Argentina 09-10	0.155	−0.0041	−0.0912
US Midwest 96	0.348	−0.0515	−0.9369
US Midwest 97-98	0.335	−0.0416	−0.7569
US Midwest 99-00	0.319	−0.0596	−1.0854
US Midwest 01-02	0.292	−0.0439	−0.7988
US Midwest 03-04	0.257	−0.0215	−0.3921
US Midwest 05-06	0.264	−0.0060	−0.1098
US Midwest 07-08	0.241	−0.0301	−0.5483
US Midwest 09-10	0.233	−0.0314	−0.5718
Share of global production		-0.2370^{***}	-4.308^{***}
		(0.0274)	(0.624)
Const		0.0311^{***}	0.557^{***}
		(0.0064)	(0.162)
Observations		15	15
R^2		0.776	0.737

Table XII: Price impact of regional rain and market shares.

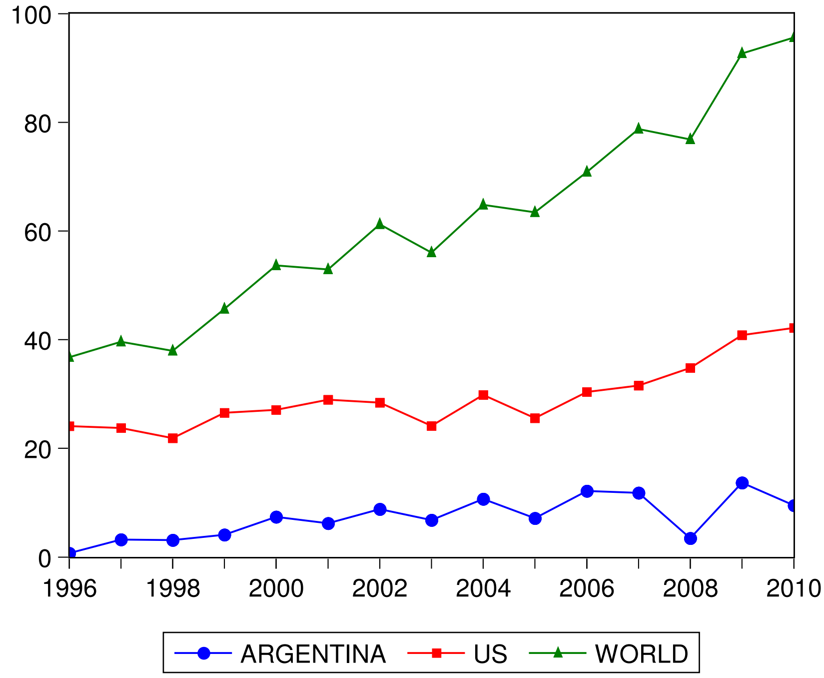

Figure 1: Soybeans, historical annual exports in millions of tons. Data was obtained from the USDA *Oilseeds Report* for December 2006, December 2010, and May 2011.

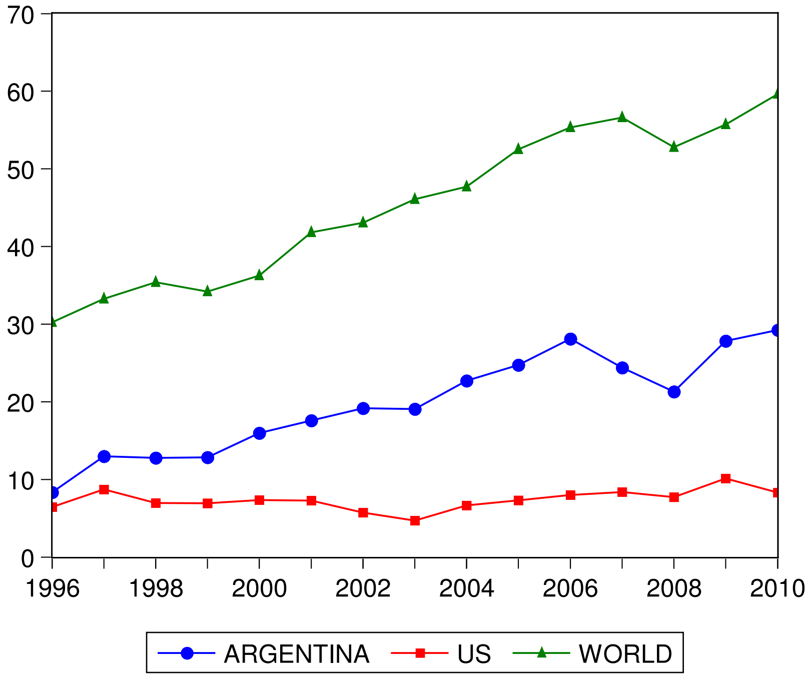

Figure 2: Soybean meal, historical annual exports, in millions of tons. Data was obtained from the USDA *Oilseeds Report* for December 2006, December 2010, and May 2011.

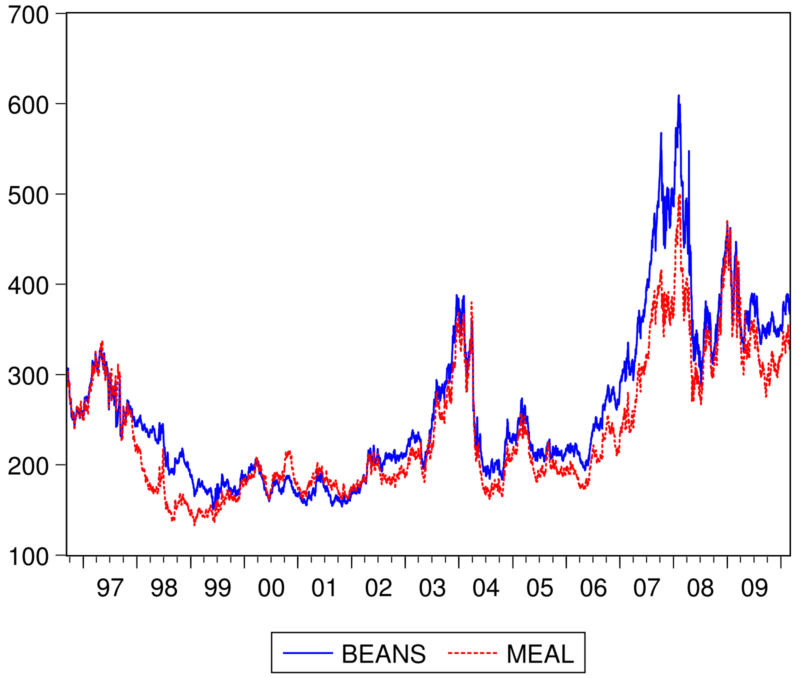

Figure 3: Historical CME futures prices. Converted to US dollars per metric ton. Nearest delivery Soybean and Soymeal contracts.

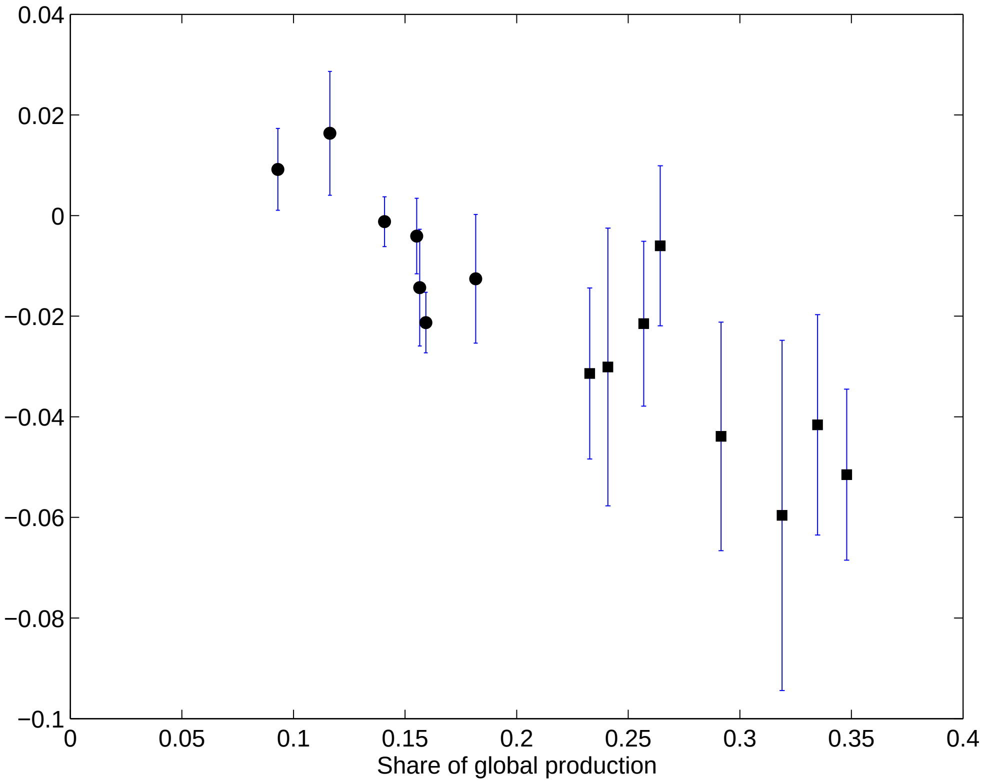

Figure 4: Impact of midsummer local rain on CME soybean price, as a function of share of global production. Circles and squares represent estimates for the central region of Argentina and the US Midwest respectively. Values are taken from Tables XI and XII.