Feasibility of new agricultural futures contract: a study in the Brazilian rice market

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INTRODUCTION

The growing importance of emerging markets such as Brazil, China and India has motivated research on these economies and their interaction with international markets. One of the issues addressed in these studies is the relevance of their derivatives markets to promote hedging opportunities, price discovery and financial stability to their economies (Hohensee and Lee, 2006; Lien and Zhang, 2008; Saxena and Villar, 2008; Kumar and Pandey, 2009). An important dimension of this problem is whether emerging economies should develop their own derivatives markets or rely on derivatives markets from developed countries. In a risk management context this point translates into a debate of whether emerging economies should have their own hedging instruments or use cross-hedging alternatives based on different exchanges or assets in developed countries.

This debate is particularly relevant for agricultural markets in developing economies, which have been through several changes lately. Using Brazil as an example, one of the main changes has been the reduction of government intervention in agricultural markets. Government has been consistently eliminating or discouraging the utilization of instruments such as production subsidies, storage and marketing loans, and payment of minimum prices. Even commodities related to domestic food security (e.g. beans, rice, corn and wheat) have been experiencing large reductions in government support, leaving producers and processors exposed to more price risk and highlighting the need of new risk management tools.

The objective of this paper is to explore risk management alternatives in developing countries, focusing on the measurement of risk, development of futures contracts, risk measurement and opportunities for own- and cross-hedging. The empirical discussion will rely on the study of rice market in Brazil, exploring price risk level and hedging opportunities

2

with a potential futures contract. This paper focuses both on measurement of price risk for several commodities in local markets and on own- and cross-hedge analysis for Brazilian rice. In addition to the economic importance of rice in the Brazilian agriculture, there is no futures market for rice in Brazil.

Different risk measures are explored, namely standard deviation, lower partial moment (LPM), value-at-risk (VaR), and conditional value-at-risk (CVaR). These four measures are used to perform a comprehensive analysis of price risk for rice and compare it with price risk for six commodities that have a futures contract in Brazil: cattle, coffee, corn, ethanol, soybeans, and sugar.

These measures will be calculated based on historical daily cash prices in their main producing areas in Brazil. The sample period contains six crop years, from 2005/06 to 2010/11. For the calculation of the lower partial moments, two targets are adopted: the production cost in the current crop year and the minimum price offered in government support programs. For the calculation of VaR and CVaR it will be considered the distribution of percentage returns with respect to the same benchmarks listed above. So the VaR will show the maximum percentage loss that producers can have with respect to their production cost and minimum price offered by government programs.

In the own- and cross-hedging analysis, the first step consists on statistical analysis of the basis for the potential rice futures contract in Brazil and the cross-hedging alternatives. Basis risk will be calculated using the traditional notion of volatility (standard deviation) and also measures of downside risk (LPM, VaR and CVaR). In the second step standard statistical techniques in futures hedging will be adopted in the estimation of optimal hedge ratios and hedging effectiveness (Chen et al., 2003). Optimal hedge ratios and hedging effectiveness of own- and cross-hedge alternatives will be generated for comparison purposes. The results and comparisons should allow us to discuss possible benefits of developing a new futures contract against the adoption of current cross-hedge alternatives.

THEORETICAL BACKGROUND

Agricultural producers have to deal with price uncertainty regularly. Given the nature of their business, there is a lag of several months between seeding and harvest. Therefore, output prices are typically unknown at the time when seeding decisions are made (Moschini and Hennessy, 2005). Marketing and risk management emerge as important skills in this environment. The amount of risk faced by producers is a relevant input for marketing and risk management decisions, which raises the question of how risk should be measured. The use of alternative hedging mechanisms are also relevant and should be considered to help producers on risk mitigating.

First, regarding risk measurement, Rachev et al. (2005) argue that volatility should be used just as a dispersion measure, and not as a risk measure. Using the volatility as a risk measure raises several concerns because the implication that agents view positive and negative deviations from the mean as equally undesirable. It also suggests that agents focus on the mean of the price distribution as a benchmark. Finally, this approach provides no information about the tails of the distribution and therefore about extreme price movements. Heavy tails in a probability distribution and asymmetry between positive and negative price changes are two common properties found in price series in financial markets (Cont, 2001). The traditional measure of volatility fails to take these issues into account as it can detect neither heavy tails nor skewness. These dimensions are relevant because they show how much probability mass is concentrated in the lower tail of the distribution, indicating the likelihood of losses. Unser (2000) argues that agents frequently perceive risk as a failure to achieve a certain benchmark, thus risk would be more accurately represented by the likelihood of losses with respect to a certain benchmark. Several studies argue that one-sided measures can be more consistent with some individuals' perceptions and are more relevant in a hedging

context than the traditional two-sided measures like standard deviation (Lien & Tse, 2002; Chen et al., 2003).

Downside (or one-sided) risk measures have been developed to address those issues. The general idea of a downside risk framework is to focus on the left side of a probability distribution, which involves primarily negative returns or losses. They are, in principle, the same notion initially discussed by Markowitz (1952, 1959) and Roy (1952). One of these downside risk measures is the lower partial moment (LPM), which originated from Bawa (1978) and Fishburn (1977). The LPM only considers deviations below a given threshold, representing the failure to achieve a certain benchmark determined by investors. The LPM of order α can be calculated as in equation (1), where *r* represents a series of returns, *B* is the investor's benchmark and *F()* is the cumulative distribution function.

$$LPM_\alpha(r; B) = \int_{-\infty}^{B} (r - B)^\alpha dF(r) \qquad (1)$$

Several risk measures are special cases of the LPM. For $\alpha = 0$ the measure is the probability of falling below the benchmark. When $\alpha = 1$, the LPM represents the expected deviation of returns below the benchmark. For $\alpha = 2$, the measure is similar to the variance, but with deviations computed only for observations below the benchmark. If $\alpha = 2$ and the benchmark is the mean of the probability distribution, then the LPM represents the semivariance as discussed by Markowitz (1952).

Another approach to measure downside risk is to focus on the tails of the probability distribution. Value-at-risk (VaR) has been used to assess the probability and magnitude of extreme losses. It measures the maximum shortfall in a portfolio during a certain period for a given probability, summarizing the expected maximum loss over a target time horizon. For example, if an asset has an one-week VaR of US$100 million with 95% confidence level, there is 95% chance that the value of this asset will not drop more than US$100 million during any given week.

VaR can be expressed in terms of returns on a portfolio instead of its monetary value, as emphasized by Liang & Park (2007). Considering $R_{t+\tau}$ as the return over a period t through $t+\tau$ and $F_{R,t}$ as the cumulative distribution function of $R_{t+\tau}$ conditional on the information available at time t, and $F_{R,t}^{-1}(\alpha)$ as the inverse function of $F_{R,t}$, the VaR of R during time horizon τ and a confidence level $1 - \alpha$ can be formulated as in equation (2).

$$VaR_R(\alpha,\tau) = -F_{R,t}^{-1}(\alpha) \tag{2}$$

A drawback of VaR is that it does not provide any information about the magnitude of possible losses beyond its confidence interval. The area of the probability distribution beyond the VaR threshold is addressed by the expected shortfall (ES), or conditional value at risk (CVaR). The CVaR measures the expected amount of loss conditional on the fact that VaR threshold is exceeded, i.e. CVaR measures the expected loss over the extreme left side of the probability distribution for a given confidence level (Liang & Park, 2007). The CVaR can be seen as a complement to VaR as it estimates expected losses in extreme risk situations beyond the VaR threshold. For example, portfolio with a 1-year VaR of \$100,000 with 95% confidence means that there is a 95% probability that this portfolio will not lose more than \$100,000 during 1 year. Assuming this portfolio has a CVaR of \$150,000 it means its expected loss if an outcome in the 5% left tail of the distribution occurs will be \$150,000.

CVaR can also be expressed in terms of the portfolio return instead of a cash amount as expressed by Liang & Park (2007) in equation (3), where $R_{t+\tau}$ denotes the portfolio return during the period between t and $t+\tau$; $f_{R,t}$ represents the conditional probability distribution function (PDF) of $R_{t+\tau}$; and $F_{R,t}$ denotes the conditional cumulative distribution function (CDF) at time t.

$$CVaR(\alpha,\tau) = -Et\left[R_{t+\tau} \mid R_{t+\tau} \le -VaRt(\alpha,\tau)\right] = -\frac{\int_{v=-\infty}^{-VaRt(\alpha,t)} vf_{R,t}(v)dv}{F_{R,t}\left[-VaRt(\alpha,\tau)\right]} = -\frac{\int_{v=-\infty}^{-VaRt(\alpha,t)} vf_{R,t}(v)dv}{\alpha} \tag{3}$$

Both VaR and CVaR are a function of confidence level and probability distributions of returns. Thus portfolios with low standard deviation can potentially have high VaR and CVaR depending on the skewness and kurtosis of returns and the confidence level (Harris & Shen, 2006). Finally, according to Artzner et al. (1999), Dowd (2005) and Liang and Park (2007), while VaR has some mathematical irregularity, such as lack of convexity, monotonicity, subadditivity, reasonable continuity, and translational invariance, CVaR meets all of these mathematical properties.

Another dimension to the study is the estimation of hedge ratio and hedging effectiveness for different alternatives of own-hedge and cross-hedge.

Basis demonstrates a systematic component with the cash prices approaching the futures as the contract matures. In additional, if seasonal patterns are observed in the cash price, this may be reflected in basis fluctuation (Garcia et al., 1984). Basis risk will be calculated using the traditional notion of volatility (standard deviation) and also measures of downside risk given by lower partial moments (LPM)[1]. The use of downside risk follows from the idea that one-sided measures can be more consistent with individuals' perceptions and are more relevant in a risk management context than the traditional two-sided measures like standard deviation (Grootveld and Hallerbach, 1999; Lien and Tse, 2002).

The existence of basis risk must be carefully managed by hedgers who must determine a specific ratio of their cash and futures position with the objective to minimize price volatility of the combined cash-futures position. This ratio is the optimal hedge ratio, which has traditionally been estimated using OLS regression on futures and cash prices. However, in the presence of unit roots and cointegration, optimal hedge ratios are estimated using equation (4).

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[1] We also consider a measure for upside risk given from the upside partial moments, which is helpful to check volatility when basis is positive.

$$\Delta C_t = \alpha + \Pi \, z_{t-1} + \phi \, \Delta F_t + \sum_{i=1}^{q} \beta_i \Delta F_{t-i} + \sum_{j=1}^{q} \gamma_j \Delta C_{t-j} + \varepsilon_t \qquad (4)$$

where ΔF_t and ΔC_t are changes in futures and cash prices; z_{t-1} corresponds to the error correction term; and ϕ is the hedge ratio.

Next step is the estimation of hedging effectiveness (E_t) to evaluate whether a combined cash-futures position exhibits less variability than a cash-only position. It is calculated from the difference between the variances of the unhedged and hedged positions as a proportion of the variance of the unhedged position (equation 5).

$$E_t = \frac{Var(\Delta C_t^u) - Var(\Delta C_t^h)}{Var(\Delta C_t^u)} = 1 - \frac{Var(\Delta C_t^h)}{Var(\Delta C_t^u)} \qquad (5)$$

where $Var(\Delta C_t^u)$ correspond to the conditional variance of the unhedged position and $Var(\Delta C_t^h)$ is the conditional variance of the hedged position.

DATA

Risk measures are calculated using daily cash prices for cattle, coffee, corn, rice, soybeans and sugar in Brazil[2], obtained from the Center for Advanced Studies on Applied Economics (CEPEA) for the period from August 1st 2005 through July 28th 2011 (1,516 observations). Those cash prices refer to main producing areas in Brazil which are also price formation regions indicated in the futures contracts traded in the Brazilian futures exchange (BM&FBovespa)[3].

Two benchmarks are considered in the calculation of LPM, VaR and CVaR: average cost of production for the areas where cash prices were obtained and minimum prices established by the federal government. Data on cost of production were obtained from Brazilian National Supply Company (CONAB) for coffee, corn, rice and soybeans, from the

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[2] Rice and sugar are expressed in R$/50kg; corn and soybeans in R$/60kg; coffee in US$/60kg; and cattle in R$/15kg. Commodities cost of production follow the same prices measures indicated.
[3] Except rice which does not have a futures contract in Brazil.

Brazilian Agricultural Confederation (CNA) for sugar, and from CEPEA for cattle. Minimum prices are a government support mechanism and are available only for coffee, corn, rice and soybeans, which were obtained from CONAB. Production costs and minimum price data are determined on an annual basis, covering each crop year from 2005/06 through 2010/11.

Basis risk analysis, hedge ratio and hedging effectiveness for own- and cross-hedge simulations are calculated considering Brazilian rice cash prices[4], BM&FBOVESPA soybean and corn futures prices and CME rough rice futures prices for the period from August 1st 2005 through July 28th 2011. Futures prices data are nearby series, with contracts rolled over on the first day of the delivery month[5].

Risk measurement in agricultural markets

Summary statistics for all commodity price series are presented in Table 1, and respective price charts are presented in Figure 1 (Appendix). Four commodities (cattle, corn, rice and sugar) show positive skewness and negative excess kurtosis, suggesting the presence of asymmetric distributions with slim tails. Coffee appears to show larger positive values of skewness and kurtosis, indicating an asymmetric distribution with fat tails. Compared to other commodities, coffee appears to exhibit greater deviations from the mean and larger portion of the distribution skewed to the right.

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[4] The same rice cash prices data used to risk measurement is used to cross-hedge simulations, but expressed in US$/50kg, same measure used to CME rice futures and BMF&BOVESPA corn and soybean futures prices.
[5] Soybeans and corn futures in the BM&FBOVESPA have seven contracts with expiration date. CME rough rice contract has six contracts with expiration date.

Table 1 - Summary statistics, commodities cash price, 2005/06 - 2010/11

	Mean	Std. dev.	Median	Max.	Min.	Skewness	Kurtosis
Cattle[1]	72.29	16.91	74.79	115.14	47.04	0.15	-1.04
Coffee[2]	147.65	49.10	133.96	349.75	92.03	2.23	5.18
Corn3	22.46	4.74	20.95	34.62	13.32	0.52	-0.75
Rice[4]	24.47	5.03	24.53	36.03	15.64	0.29	-0.77
Soybeans[4]	38.44	8.22	41.25	53.41	23.10	-0.23	-1.44
Sugar[3]	25.12	11.07	21.64	46.36	11.99	0.58	-1.16

Note: [1] R$/15kg; [2] US$/60kg; [3] R$/50kg; [4] R$/60kg.

Price risk is first discussed across commodities using the standard deviation (volatility) and, more meaningfully, the coefficient of variation. Table 2 presents results for these two measures for the whole period. Standard deviation indicates that coffee prices showed the highest dispersion around the mean in comparison to other commodities, while rice and corn showed the lowest volatility. However, as all data series are in their original basis, standard deviation results tend to be higher for commodities whose prices are higher, as coffee and cattle. Hence the coefficient of variation offers a more meaningful comparison of price variability across commodities. Values for the coefficient of variation presented in Table 2 indicate that sugar presents the most price variability, while all other commodities showed similar results. Thus the coefficient of variation suggests that rice presented essentially as much risk as all other commodities but sugar between 2005/06 and 2010/11.

Table 2 - Standard deviation and coefficient of variation of selected commodities, 2005/06 - 2010/11

	standard deviation (%)	coefficient of variation (%)
Cattle	16.910	23.580
Coffee	49.097	23.134
Corn	4.737	21.366
Rice	5.030	20.230
Soybeans	8.220	21.180
Sugar	11.074	44.076

Standard deviation and coefficient of variation consider deviations both above and below the mean, which implies that profit opportunities as prices rise above the mean are also included in the calculation of risk. In order to focus only on downside deviations three other risk measures are calculated: LPM, VaR and CVaR. For all of them only deviations below a certain benchmark will be considered in the calculation of risk. Two benchmarks are used: cost of production and government's minimum price. Table 3 presents results for the LPM with all benchmarks. It can be seen that results vary across commodities and also across benchmarks, i.e. the magnitude of the LPM can change depending on the benchmark. In terms of risk assessment, coffee and rice emerge as the commodities with largest price deviations below the benchmark when cost of production and government's minimum price are considered. Note also that cattle, corn, soybeans and sugar exhibit little price variability below their costs of production and the government's minimum price.

Table 3 - Lower Partial Moments (LPM) for different benchmarks, 2005/06 - 2010/11

	Benchmarks	
	cost of production	government's minimum price
Cattle	0.000	n/a
Coffee	21.144	2.288
Corn	1.687	0.008
Rice	8.197	3.643
Soybean	0.911	0.000
Sugar	0.056	n/a

Even though coffee and rice appear to show the most price variability below their costs of production and government's minimum prices, the pattern of deviations from the benchmarks differs over the years. While coffee prices were below these benchmarks mainly in one crop-year, rice prices were regularly below production costs during the sample period, as illustrated in Figure 1 (Appendix). That is, coffee might have shown larger deviations

below the benchmarks, but rice exhibited those downside deviations more consistently over time. Similar findings emerge when government's minimum prices are adopted as benchmark, as can be seen in Figure 2 (Appendix).[6]

When risk is measured as downside deviations from a certain benchmark (LPM) as opposed to all deviations from the mean (standard deviation, or volatility), rice emerges as one of the riskiest commodities in Brazil between 2005/06 and 2010/11. However, it remains to be explored how much producers can lose if their prices fail to achieve a certain benchmark. The calculation of VaR and CVaR can shed light on this issue. In this study the VaR and CVaR are calculated as percentage deviations from a benchmark.

Table 4 presents results for the VaR using a 95% confidence level. When cost of production and government's minimum price are used as benchmarks, rice exhibits the largest maximum losses within the 95% interval. Rice producers could have obtained prices as low as 47.9% below their cost of production or 32.2% below government's minimum price during the sample period.[7] In contrast, calculated VaR for other commodities showed absolute values below 30% and 2% using the cost of production and government's minimum prices as benchmarks, respectively (Table 4).

Table 4 - Value-at-risk (VaR) for different benchmarks, 2005/06 - 2010/11

	Benchmarks	
	cost of production	government's minimum price
Cattle	-20.9%	n/a
Coffee	-29.0%	-1.7%
Corn	-36.1%	-1.6%
Rice	-47.9%	-32.2%
Soybean	-28.0%	0.0%
Sugar	-18.0%	n/a

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[6] During the sample period the Brazilian rice market was characterized by excess supply and constant imports of cheaper rice from Argentina and Uruguay.
[7] Note that government's minimum price is used here as a reference to investigate downside risk. Obviously producers would apply to receive the minimum price rather than taking a loss.

Calculation of the CVaR shows similar results, with rice exhibiting larger expected losses beyond the VaR threshold compared to other commodities. Focusing again on the cost of production and government's minimum price as benchmarks, prices received by rice producers could have been, on average, 56.3% and 40.8% below the benchmark if the VaR threshold had been breached (Table 5). Conversely, absolute values for CVaR for the other commodities were mostly 30-40% when production cost was the benchmark and less than 15% when government's minimum price was the benchmark (Table 5).

Table 5 - Conditional value at risk (CVaR) for different benchmarks, 2005/06 - 2010/11

	Benchmarks	
	cost of production	government's minimum price
Cattle	-28.9%	n/a
Coffee	-38.3%	-13.3%
Corn	-47.7%	-14.8%
Rice	-56.3%	-40.8%
Soybean	-37.0%	-4.0%
Sugar	-34.6%	n/a

Results from VaR and CVaR are consistent with findings from the LPM analysis suggesting that rice exhibits large downside risk. For example, between 2005/06 and 2010/11 there was a 95% probability that the lowest price that rice producers would receive was 47.9% below their cost of production. In the same context, the lowest price that coffee, corn and soybean producers would receive was 28-29% below their cost of production (Table 4). If the market price had fallen outside the 95% confidence interval, the expected price that rice producers would have receive would have been 56.3% below their cost of production. As for coffee, corn and soybean producers in the same situation, their expected prices would have been 37-39% below their cost of production. These results contrast with the discussion of risk based on the coefficient of variation, which showed very similar numbers for these four

commodities (Table 2), suggesting that risk assessment can yields distinct conclusions when risk is viewed as downside deviations with respect to a certain benchmark.

Hedging alternatives for Brazilian rice

Own- and cross-hedge alternatives for Brazilian rice exhibit interesting results. During the sample period, basis is mostly negative using CME rice futures to hedge Brazilian rice as well as cross-hedging rice with the Brazilian soybean futures contract. Basis in cross-hedge operation using the Brazilian corn futures is predominantly positive as illustrated in Figure 3 (Appendix). Table 6 shows summary statistics of basis calculated as the difference between rice cash price in Brazil and (i) rice futures price at the CME Group, (ii) corn futures price at BM&FBOVESPA and (iii) soybean futures price at BM&FBOVESPA. Basis for the three contracts show large ranges of approximately US$13-14/50kg. Coefficients of variation suggest that basis relative to rice and corn futures exhibit similar overall variability, while basis relative to soybean futures show smaller variability. However, LPM calculations indicate that basis relative to soybean and rice futures exhibit more variability below zero, while basis relative to corn futures exhibit more variability above zero.

Table 6 – Summary statistics of daily basis for each own- and cross-hedging alternative, 2005-2011

	CME rice	BMF corn	BMF soybean
Minimum	-9.950	-4.560	-14.250
Maximum	3.640	8.850	-0.120
Average	-1.863	2.687	-6.099
Standard Deviation	2.062	2.785	3.155
Coefficient of Variation	-1.125	1.046	-0.518
Lower Partial Moments	2.690	0.873	6.831
Upper Partial Moments	0.704	3.771	0.001

Note: LPM and UPM considered basis below and above zero, respectively.

Before the discussion of hedge ratios and hedging effectiveness, it is necessary to test the price series for unit root and cointegration. Augmented Dickey-Fuller (DFA) tests indicate that all price series are stationary in first difference, but not in level. Johansen cointegration tests suggest the existence of one cointegration vector between rice cash prices and CME rice futures prices, but finds no evidence of cointegration between rice cash prices and corn and soybean futures prices (Table 7).

Table 7 – Results from Johansen cointegration test for rice cash prices and each futures prices, 2005-2011

	H_0	H_A	λ_{trace}	Prob.	$\lambda_{max.}$	Prob.
CME rice	$r \leq 0$	$r = 1$	24.543*	0.002	21.625*	0.003
	$r \leq 1$	$r = 2$	2.918	0.088	2.918	0.088
BMF corn	$r \leq 0$	$r = 1$	6.974	0.581	5.775	0.642
	$r \leq 1$	$r = 2$	1.199	0.274	1.199	0.274
BMF soybean	$r \leq 0$	$r = 1$	9.472	0.324	8.626	0.319
	$r \leq 1$	$r = 2$	0.846	0.358	0.846	0.358

Optimal hedge ratios are estimated using an error correction model for rice cash prices and rice futures prices, and OLS regressions for rice cash prices and corn and soybean futures prices. Estimated hedge ratios from each regression are presented in Table 8, along with their respective hedging effectiveness.

Table 8 – Optimal hedge ratio and hedge effectiveness obtained from the regression of rice cash and each futures prices considered, 2005-2011

	CME rice	BMF corn	BMF soybean
Optimal hedge ratio (φ)	6.65%	1.67%	1.97%
t statistic	[4.445]	[1.018]	[2.092]
Prob.	0.000	0.309	0.037
F statistic	[12.744]	[16.757]	[5.952]
Prob.	0.000	0.000	0.000
Hedge Effectiveness (E*)	1.35%	0.07%	0.30%
Coefficient of determination (R^2)	0.031	0.032	0.010

All alternatives show low optimal hedge ratios for Brazilian rice. Despite the existence of long run relationship with CME futures prices, domestic rice exhibits a small hedge ratio (about 6%). Optimal hedge ratios for local grains futures contract are even smaller, suggesting about 1% of hedge position with corn futures and 2% with soybean futures. Results are similar for hedging effectiveness, which is almost zero in all cases.

CONCLUSIONS

The purpose of this study was to discuss the development of new futures contracts using the rice market in Brazil as an example. This paper focused on two important issues: the amount of risk in the market that would generate demand for risk management tools, and the competition from cross-hedge using existing futures contracts.

Measures of price risk show interesting results. When the coefficient of variation is considered, rice seems to have similar levels of price risk in comparison to other commodities in Brazil. Conversely, when downside risk measures are used (LPM, VaR and CVaR), results suggest that rice has larger risk (deviations below the benchmarks) and greatest potential losses than any other commodity.

The great magnitude of downside risk for Brazilian rice is indicative of large price uncertainty over a crop year, and suggests the need for local production chain to develop new risk management tools to reduce their risk exposure, e.g. a local futures contract developed to meet the characteristics of local producers, industry, and traders.

The cross-hedge analysis provide further insights. First, large basis variability for all cross-hedges is a first sign of the complexity to hedge Brazilian rice with other futures contracts. Furthermore, regression analysis show low optimal hedge ratios, along with hedging effectiveness that are close to zero. These findings indicates poor prospects for cross-hedging in the Brazilian rice market.

In general, results provide evidence of large price risk in the Brazilian cash market for rice and no effective cross-hedging opportunity for Brazilian rice producers. Although other issues must be considered to assess if a new futures contract may generate liquidity and successfully provide a new risk management tool for rice producers, current findings point to a promising scenario for the development of a Brazilian rice futures contract.

Overall, our findings about the development of new futures contracts against the adoption of existing cross-hedging alternatives can offer new insights on the debate about the importance of derivatives markets in developing markets (Lien and Zhang, 2008). Further analysis can explore other cross-hedging possibilities and different hedging horizons, in addition to other issues that affect the success of new futures contracts.

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APPENDIX

Figure 1 – Daily cash prices and cost of production, 2005/06 - 2010/11
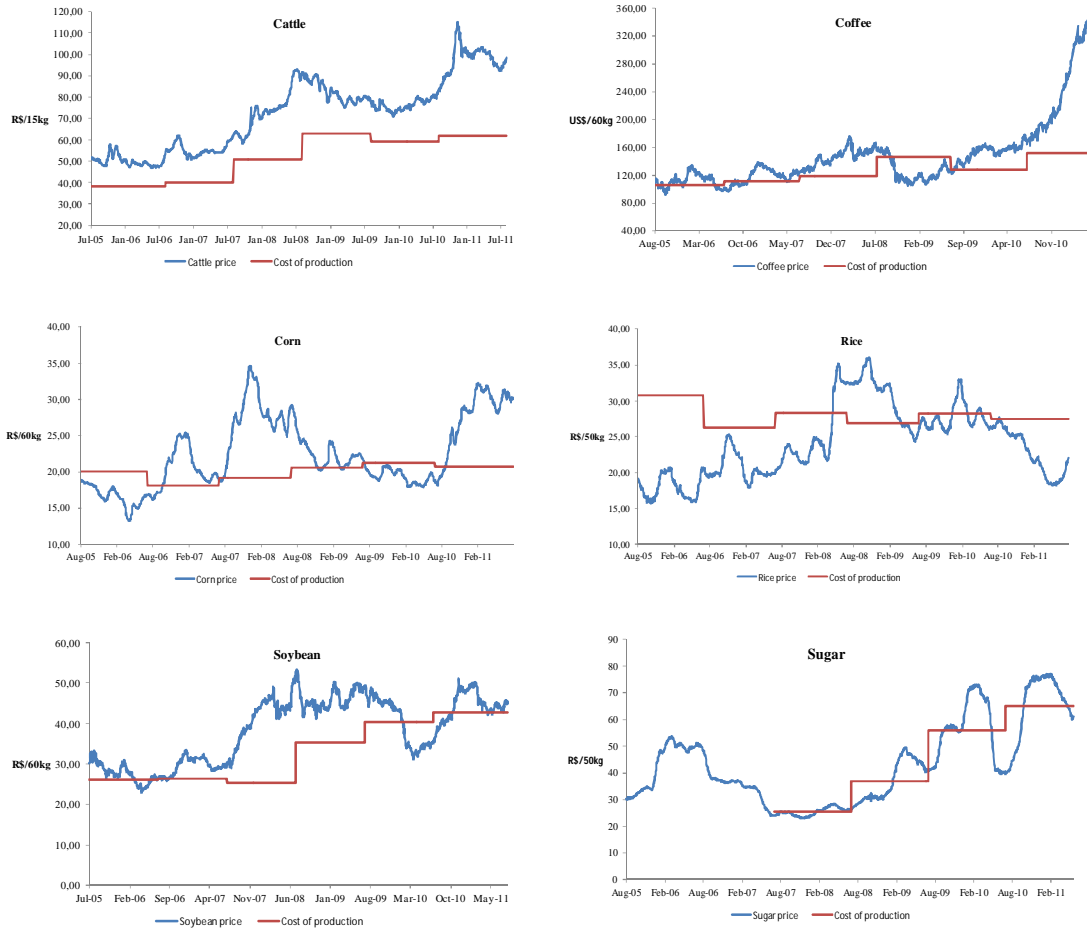
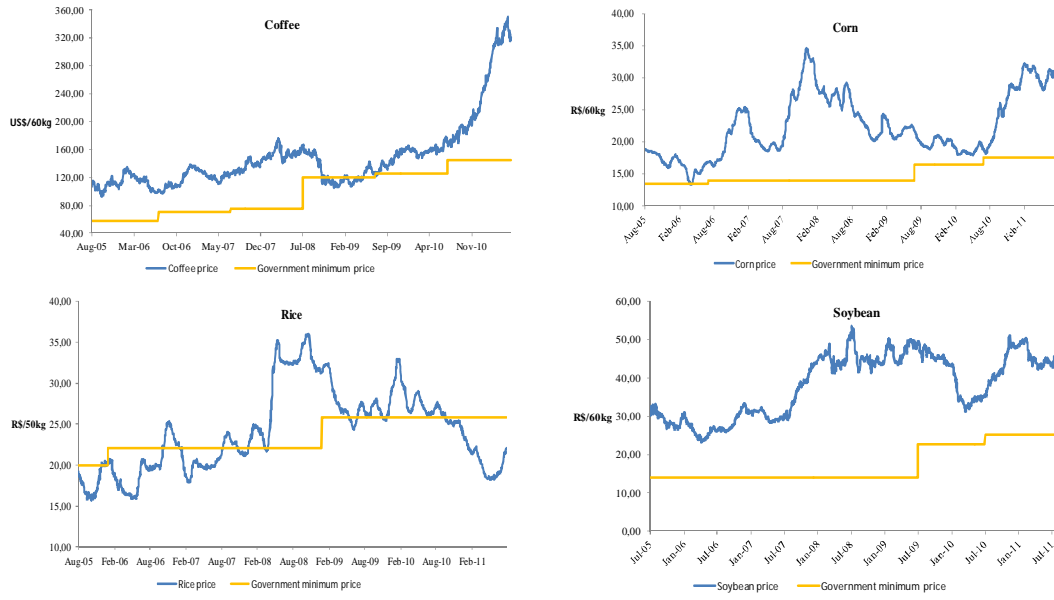Figure 2 – Daily cash prices and government's minimum price, 2005/06 - 2010/11

Figure 3 – Basis between rice cash price and futures prices, 2005-2011

Basis - cash rice vs CME rice futures

Basis - cash rice vs BMF soybean futures

Basis - cash rice vs BMF corn futures