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Measuring the functional efficiency of agricultural futures markets

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This article presents a method for measuring the functional efficiency of agricultural futures markets in terms of social welfare using a standard futures market structural model. Employing the concept of social surplus, it can be shown that, when futures prices are used to estimate future spot prices, the errors in prediction produce to some degree resource misallocation, which in turn results in welfare losses. Therefore, the social welfare associated with the presence of futures markets can be measured using a Social Loss index. The indicator was calculated for the period 1975–2015 and for several subperiods, which allow us to analyse functional efficiency before and after the 2007–2008 spikes in the prices of agricultural commodities. Futures contracts for 12 products are evaluated. The products are grouped in three different categories: 'soft products', 'livestock' and 'grains and oilseeds'. The results indicate that livestock contracts tended to be more efficient than the rest of the contracts during the whole period, but in 2008–2015 their efficiency decreased vis-á-vis the rest of the products. Nevertheless, 2008–2015 proved to be the most efficient subperiod, confirming the remarkable development of agricultural futures markets over time.

Key words: agricultural futures markets, functional efficiency, futures prices, social loss, social welfare.

1. Introduction

Agricultural market pricing in futures markets have received increasing attention in the international focus because of the negative consequences that price volatility could have on farmers and in the access to food in the poorest economies. In 2013, most food commodity prices were two or even three times higher than they were a decade earlier (Baffes and Dennis 2013). Beginning in late 2007, prices increased and, in general, agricultural futures markets were growing quickly. For instance, from June 2004 to June 2006, open interest for wheat futures increased by 275 per cent (Sanders *et al.* 2010), and by around 100 per cent for corn, soya bean, and soya bean oil futures markets. During 2007 and 2008, a period of instability in food prices was evident. The news media advertised about the negative effects of high and increasing food prices on the consumers, national governments pursued policy interventions to stabilise and reduce prices, and international organisations warned the world about the negative effects of high and

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increasing food prices (Pinstrup-Andersen 2014). It should be noted that agricultural prices are generated in highly competitive international markets with many producers and buyers exchanging huge quantities of each commodity at prices that are quite volatile.

The price volatility ‘passes through’ from international to national markets and is influenced by the degree of openness and market integration of the country and further ‘passes through’ to farmers, consumers and traders, who will depend on national and local institutions and infrastructure, and on the efficiency of domestic markets (Pinstrup-Andersen 2014). Within this context, constant price fluctuations are inevitable, given that production decisions are based on prices from the previous season, which in turn are the result of supply and demand conditions that vary from season to season. However, this price volatility has different effects depending on the country. It is predominantly farmers in less developed countries who are caught in a difficult situation, while developed countries often have pricing and farm-income policies which protect them against these variations. Instability in local and world food prices is a serious problem, which primarily affects food security and hunger in developing countries. The exposure of these countries to the risks, and the inability to manage those risks can jeopardise development goals, including economic growth and poverty reduction (World Bank 2013).

When we refer to high food prices, it is important to highlight that the consequences of a policy to maintain low prices is not recommended because it could be counterproductive to the farmers of low-income countries. According to Pinstrup-Andersen (2014), treating smallholders as consumers rather than producers in price-stabilisation policies that keep prices low is not conducive to agricultural development because they reduce the incentive to invest in rural areas. As can be seen, policies that maintain low prices does not seem to be a solution for the risk that price instability generates, especially because those policies do not reduce instability itself. Agricultural prices have always been volatile, and consequently learning to live with price volatility is one of the main objectives that international and national food policies should focus on. For this reason, the ability to understand market behaviour could be more important than controlling price rises (Pinstrup-Andersen 2014). In this context, it is easier to grasp the relevance of the functional efficiency index presented in this paper, as it helps to evaluate the usefulness of agricultural futures prices as sources of information about the behaviour of agricultural prices over time and as effective hedging instruments.

In this article, we aim to analyse how the agricultural price instability affected the functional efficiency of its standardised markets, to determine how reliable futures prices are to predict spot prices at the expiration date of each contract in unstable periods. In this regard, we evaluate the functional efficiency of agricultural futures markets both before and after the alarm over the international food price surges of 2007–2008 (Ano Sujithan *et al.* 2013; Warr 2014).

For this purpose, we selected 12 agricultural futures markets and six maturities for each – live cattle, feeder cattle, lean hog, coffee, soya bean, soya bean meal, soya bean oil, wheat, corn, cocoa, orange juice and sugar No. 11 – with data from 1975 to 2015[1]. Classifying the 12 futures markets in three groups of products *softs*, *livestock* and *grains and oilseeds*, we were able to observe different levels of functional efficiency in each group as well as in each market.

With this in mind, the period under study does not include the previous period of severe price growth and instability during the 1970s, although it was structurally different from the situation in 2007[2]. An analysis of futures markets prices will allow us to understand how the functional efficiency of agricultural futures markets was affected by the developments that produced the trend change after 2007 according to the product and its type.

The term *functional efficiency* refers to the efficiency with which futures markets perform the functions of price risk transfer and price discovery. Regarding the transfer of price risks, participants seek to protect themselves from price variability, and the efficiency of the hedging instrument depends on the relative variation between the prices of futures contracts and the prices in the physical market. Price discovery refers to the fact that each participant in the futures markets acts according to all the available information and their own estimates on future price fluctuations. In this article, the functional efficiency of agricultural futures markets is assessed by estimating the social loss derived from allocation errors that result when futures contracts prices are used as estimators for spot prices in the future.

In the following section, we review previous research on the topic, and in the third section, we present the model used as the basis for our empirical exercise. Section four consists in the quantification of a measure of social welfare loss in agricultural futures markets. The last section includes conclusions and future lines of research.

2. Previous research

There is an ample body of research on the efficiency of commodities futures markets. Timmermann and Granger (2004) researched efficiency in commodities futures markets by studying whether each of these markets is, or is

[1] In a futures contract, maturity k refers to the distance of the contract from a given time to the expiration date. So, $k = 3$ means that three expiration dates have yet to pass until the contract expires. For more information about each product's maturities and expiration dates, see the web page of the Intercontinental Exchange (ICE) and the Chicago Mercantile Exchange (CME).

[2] Since the 1970s, the number of futures markets grew as well as the number of participants referred to respectively as open interest and trade volume (Carlton 1984). These changes increased the relevance of futures markets for policy concerns and the need to develop a regulatory framework that consequently affected market structure in the following decades.

not, using the efficient market hypothesis (EMH). Many other authors such as Peroni and McNown (1998), Switzer and El-Khoury (2007), Maslyuk and Smyth (2009) and Kawamoto and Hamori (2011) have focused on analysing the efficiency of energy futures markets from a theoretical perspective, using methodologies that are also relevant to agricultural markets research. The analysis carried out by Kawamoto and Hamori (2011) is closest to our approach insomuch as they also used a sample of futures contracts with different maturities.

A considerable number of publications have shed light on the importance of price discovery and hedging strategies in agricultural futures markets for the agricultural industry[3]. Of more relevance to our research are papers which have studied the efficiency of agricultural futures markets using recent data from spot and futures prices. For instance, Chowdhury (1991), McKenzie and Holt (2002) and Kumar and Pandey (2013) tested the short- and long-run market efficiency and unbiasedness of a group of agricultural futures markets using cointegration procedures, and Wang and Ke (2005) studied efficiency in the Chinese agricultural futures markets. Another interesting contribution to the topic was recently proposed by Kristoufek and Vosvrda (2014), who developed a model for measuring efficiency in futures markets commodities by means of an alternative efficiency index. They utilised a newly developed efficiency index to determine the market efficiency of 25 agricultural and energy commodities. Their index is different from ours and, consequently, the results differ.

As can be seen, a substantial body of literature has presented multiple methodologies and tests for measuring efficiency in futures markets. Unlike the literature just reviewed, we employ a generic structural model of futures markets in which efficiency is measured with an indicator that evaluates the functional efficiency of futures markets in terms of social welfare. This model is also applicable to different types of commodities, such as metals, agricultural products and energy products.

The basic model used in this research was originally developed by Stein (1961, 1986). Part of this model has been used by different authors over the years: Brooks (1989) and Stein (1991) applied it to financial futures markets, Hong (1989) used the model to study nonfinancial futures, Avsar and Goss (2001) analysed the informational efficiency of electricity futures contracts, Pennings and Garcia (2010) examined the determinants of hedging behaviour heterogeneity, and García-Verdugo and Consuegra (2013) focused on energy futures contracts.

Some additional comments about our methodological choices are required. VAR models have been recommended by different authors since the work of Canarella and Pollard (1985) to evaluate the EMH in commodity futures markets. However, our focus is to provide a quantitative estimate of

[3] The literature focus on futures markets for the agricultural industry is extensive. For a good updated summary of the topic, see Tomek and Kaiser (2014).

functional efficiency rather than VAR models, which demands a different methodological approach. Our paper does not aim to capture the linear interdependencies among different agricultural futures markets, and therefore, it was a more parsimonious solution to select a theoretical model as a solid conceptual base for our functional efficiency index without the need to estimate the parameters of the model. This approach is nonetheless more appropriate than the use of more complex models to identify the relative levels of functional efficiency between different futures contracts and maturities using its prices as estimators for spot prices in different periods.

The Stein model is based on the optimisation of individual decisions made by different market participants and has several useful features. First, it explains the variables that determine equilibrium prices, equilibrium open interest and the variability of prices. Second, it incorporates exogenous and endogenous expectations as well as different forecasting abilities. Finally, it can be used to analyse the ex-post contribution of futures markets to social welfare through the optimal intertemporal allocation of resources.

3. The social loss index

The basic social loss model has two periods. In period t, producers and consumers decide the proportion of their commercial positions they want to hedge with futures, and speculators make their investment decisions. In period $t + 1$, commodities are exchanged in the physical market and open positions in futures contracts are closed. Commercial participants are attracted to futures markets to protect themselves from price risks. On the contrary, it is the variability of these same prices which attracts speculators and determines their expected profits. As a result of the participant's hedging decisions, optimal levels of production as well as optimal positions in the futures market are obtained.

Literature on commodities futures markets traditionally assumes that speculative transactions result in net long speculative positions. Accordingly, the only commercial participants included in Stein's model are assumed to hold a net short position in futures contracts; that is, they are sellers hedging against the risk of falling prices. We assume that the quality of the hedging instrument is perfect for simplicity's sake, but the relaxation of this assumption would not alter the conclusions of our study. Market equilibrium is obtained when the supply function equals the demand function. In the model, futures prices determine production, while consumption exogenously equals production. Accordingly, the functional efficiency of futures markets is assessed by estimating the social loss derived from allocation errors that are committed when the prices of futures contracts are used to estimate prices in physical markets.

Following Stein (1986), we assume that the loss of social welfare or social loss is represented by the expression:

$$L(t+1) = C[p(t+1) - q_{t+1}(t)]^2, \text{with } C = \frac{1}{2(b+c)} \quad (1)$$

Ex-post social loss $L(t+1)$ is a multiple C of the square of the price deviation between the subsequently realised cash price $p(t+1)$ and the futures price $q_{t+1}(t)$. Stein (1986) defines the social loss statistic SL as the ratio of the social loss $L(t+1)$ to the minimum or inevitable social loss L_0. Using Equation (1), it can be seen that the expected social loss $E[L(t+1)]$ is equal to the constant C times the mean-squared error (MSE) of the price forecast for $t+1$. On the other hand, the expectation of the inevitable social loss $E(L_0) = \mathrm{EC}[\varepsilon(t+1)]^2$ can be written as C times MSE_0. Therefore, the value of C is not needed to compute the SL statistic for the estimation of social welfare loss:

$$\mathrm{SL} = \frac{E[L(t+1)]}{E(L_0)} = \frac{\mathrm{EC}[p(t+1) - q_{t+1}(t)]^2}{\mathrm{EC}[\varepsilon(t+1)]^2} = \frac{\mathrm{MSE}(t+1)}{\mathrm{MSE}_0} \quad (2)$$

Now we move from two periods to a more realistic k periods (which represent as many maturities) and define the empirical equivalent of MSE(k) as:

$$\mathrm{MSE}(k) = \frac{1}{n}\sum_{t=1}^{n}[\ln p(t+k) - \ln q_{t+k}(t)]^2 \quad (3)$$

where n is the number of observations in the data. MSE(k) is the mean-squared error derived from the estimation of the spot price in period $t+k$ (the expiration date) using the price in time t of the futures contract which expires k periods later[4]. On the other hand, MSE(1) will be used as an empirical proxy of the unobservable inevitable expected social loss MSE_0. Thus, the last term in (2) can be rewritten as

$$\mathrm{SL}(k) = \frac{\mathrm{MSE}(k)}{\mathrm{MSE}_0} = \frac{E[p(t+k) - q_{t+1}(t)]^2}{E[\varepsilon(t+1)]^2} \quad (4)$$

Now, the empirical approximation to SL(k) in (4) includes squared terms that exaggerate the absolute differences between the values of the statistic and reduce the informative content of the computed mean of forecast deviations. Following the method applied by Ma (1989) in her efficiency contrasts, the squared root of the mean-squared error can be used as an alternative:

[4] Or put it in another way, the futures contract at time t has a maturity of k.

$$\mathrm{RMSE}(k) = \left[\frac{1}{n}\sum_{t=1}^{n}[\ln p(t+k) - \ln q_{t+k}(t)]^2\right]^{\frac{1}{2}} \quad (5)$$

So that:

$$\mathrm{SL}(k) = \frac{\mathrm{RMSE}(k)}{\mathrm{RMSE}(1)} \quad (6)$$

3.1 Results: the SL index in agricultural futures markets

We apply the SL model to assess the functional efficiency of a group of 12 agricultural futures markets using monthly prices data from 1975 to 2015 downloaded from the *Bloomberg* database. The analysis is carried out for different groups of products, thus allowing us to study the differences in functional efficiency across contracts and groups. The futures contracts selected for the empirical analysis are traded in the Intercontinental Exchange (ICE), the Chicago Mercantile Exchange (CME) and the Chicago Board of Trade (CBOT), which is part of the CME Group. Twelve products and six maturities for each futures contract were selected: three *livestock* products from the CME (feeder cattle, live cattle and lean hog[5]), five *grains and oilseeds* products from CME (wheat, corn, soya bean, soya bean oil and soya bean meal) and four *soft* products traded in the ICE (coffee, cocoa, orange juice and sugar No. 11)[6].

Following Kumar's (1991) approach, we use futures prices corresponding to the last trading day of each month – for the month prior to expiration as well as for the previous five expirations – during the period of study. Kumar tested the hypothesis that the last futures price of each month contains all relevant information up to that moment, which is why those prices should be more accurate in predicting prices. He concluded that price predictions made during the last trading day were superior to those obtained with alternative methods. In this regard, this paper uses each contract prices data of the last

[5] In 1997, the Chicago Mercantile Exchange (CME) switched completely from live hog to lean hog futures contract. So, the data used in this article refer to live hog before 1997 and to lean hog after 1997. The most remarkable changes were as follows: cash settlement to a 'lean hog index', meaning that the futures price will converge to the index; prices represent a lean value versus a live value; contract consists of 40,000 pounds of carcass instead of live weight; contracts expire the 10th business day of month; options expire same day as futures contract; no price limit the last two days of trading.

[6] The detailed specifications of these contracts can be found in their respective websites. Suffice it to say here about the more industry-specific terms that 'feeder cattle' are steers or heifers that are fattened prior to slaughter; 'live cattle' referred only to live steers until August 2015 (from then on includes live heifers); and 'lean hog' are butchered pigs regardless of paunch which replaced the famous 'pork bellies' futures contract.

day of the month to predict the expiration date price. The better it performs, the more efficient the market is.

Figure 1 shows the SL (k) index for 6 maturities of each product for the period 1975–2015 and three subperiods, two of them until the break year of 2007 (1975–2007 and 1998–2007) and a third subperiod until 2015 (2008–2015). As a significant increase in agricultural spot and futures prices began in 2007 (Sanders *et al*. 2010; Baffes and Dennis 2013; Pinstrup-Andersen 2014; Warr 2014), the period analysis allows us to compare how efficiently agricultural futures markets performed both before and after the 2007 breaking point. Both the 1975–2007 and the 1998–2007 subperiods show the market efficiency before the price spikes, but the shorter period provides a more balanced comparison point with the 2007–2015 subperiod so that more robust conclusions can be drawn. Considering that lower SL values represent a higher functional efficiency of the market, products are ranked accordingly with the most efficient at the bottom of each graph and the least efficient at the top.

As expected, for the whole period 1975–2015 as well as for the subperiods, SL values increased with the distance to contract maturity, showing that futures prices see their capacity for prediction reduced when k increases. Most of the products reduced its efficiency approximately by 25 per cent when maturity changes from $k = 2$ to $k = 3$. However, the reduction in efficiency is progressively less pronounced for $k > 3$. The average efficiency reduction is around 15 per cent when the maturity increases from $k = 3$ to $k = 4$, 13 per cent from $k = 4$ to $k = 5$, and 9 per cent from $k = 5$ to $k = 6$.

On the other hand, Figure 1 also shows that, in terms of social loss, *soft* and *livestock* contracts were more efficient (their SL values were lower) than *grains and oilseeds* futures contracts especially before 2007. Only in 2008–2015 when $k = 2,3,4,5,6$ and in 1975–2007 when $k = 5$, one product from *grains and oilseeds* occupies the third place in efficiency. On the contrary for almost every period and maturity *livestock* present the best results in efficiency. This higher functional efficiency means that they provided more accurate guidance to the participants in their respective physical markets. Garcia *et al*. (2015) could in part explain the lower efficiency of *grains and oilseeds* futures contracts. Their paper shows that between 2005 and 2010 CBOT corn, wheat and soya bean futures contracts exhibited convergence failure to the price of the underlying commodity on the expiration date. The nonconvergence arises in equilibrium when the market price of physical grain storage exceeds the cost of holding delivery instruments. Accordingly, the habitual position of grains as the less efficient markets might be partly related to this failure.

It is easier to see the differences in functional efficiency in the ranking by products shown in Figure 2, which presents, for each contract and period, the mean of the SL(k) values across maturities. This second figure provides a simpler way of comparing the functional efficiency of the contracts without the noise added by the consideration of different maturities. For the complete

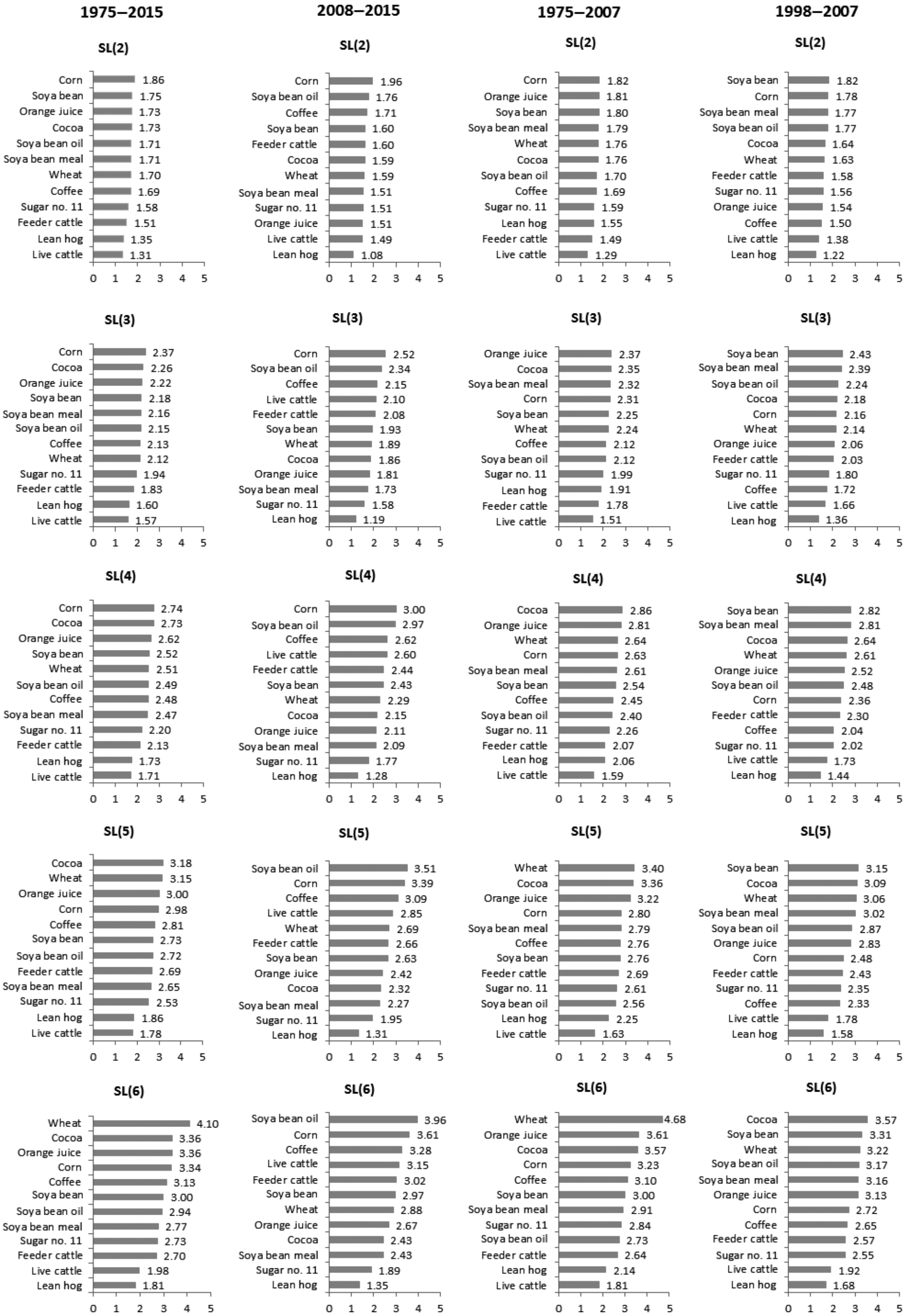

Figure 1 SL values for maturities 2 through 6 for each period and subperiod.

period under study (1975–2015), lean hog was the most efficient market, followed by live cattle, feeder cattle and sugar, all of them with a mean SL value below 2.2. Then we find soya bean, soya bean meal, soya bean oil and

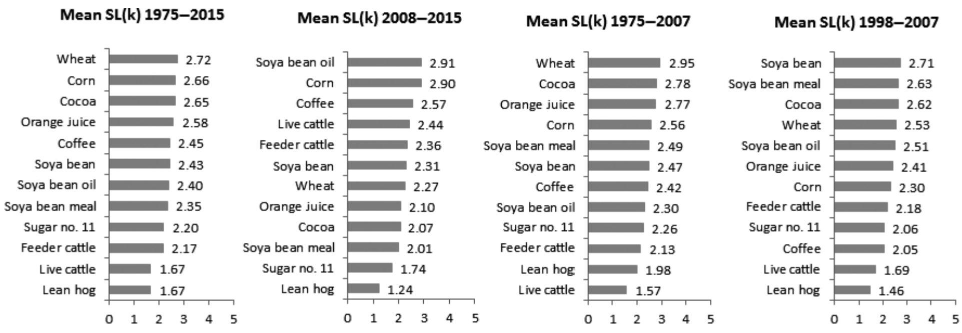

Figure 2 Mean SL values over different maturities for each period and subperiod.

coffee contracts, with values around 2.4. After a jump upwards, we find the rest of the contracts, with values between 2.6 and 2.7.

Figure 2 also shows that the ordinal ranking and the mean SL values of specific contracts change perceptibly before and after 2007. It is quite significant that the groups of products with higher or lower functional efficiency remains the same, with the exception of the 2007–1975 subperiod, where in average *soft* and *grains and oilseeds* behave similarly in efficiency. However, the worst performance in efficiency was in the 2007–1975 subperiod. Due to the improvement in agricultural futures markets functional efficiency throughout the time, the subperiod up to 1998–2007 present better indexes than 2007–1975[7]. In the 1998–2007, subperiod lean hog (1.46) and live cattle (1.69) had the lower mean SL values, followed by coffee (2.05), sugar (2.06) and feeder cattle (2.18). The results showed the good performance of *livestock* markets in this subperiod. The rest of the markets presented an efficiency between 2.30 and 2.71. After 2007, in the 2008–2015 subperiod, the lean hog increase its efficiency with a SL value of 1.24 maintaining the position of the most efficient market of the group. The real improvement was evident in *grains and oilseeds* and *soft* markets, where sugar, soya bean meal, cocoa and orange juice present SL value mean between 1.74 and 2.10, followed by wheat and soya bean. On the contrary, feeder cattle and live cattle reduce their efficiency drastically with mean SL values of 2.36 and 2.44.

In any case, the functional efficiency of agricultural futures contracts as a group improved after 2007, as the lowest mean SL value was reduced by almost 15 per cent (1.46–1.24) between 1998–20017 and 2008–2015, and the same value dropped by 21 per cent (1.57–1.24) between 1975–2007 and 2008–2015. Actually, the mean SL values for some contracts such as feeder cattle, soya bean oil, corn, coffee and live cattle went up during 2008–2015, but the

[7] The SL index averages in the group of the studied agricultural futures markets were higher for the subperiod preceding 1998–2007. In 1975–1987 and 1988–1997, the SL index averages were 2.57 and 2.31, respectively, while in 1998–2007 and 2008–2015, the index averages were 2.26 and 2.24.

improved functional efficiency of the other markets – especially those with higher mean SL values in preceding periods, like the grains, but also lean hog, sugar, orange juice and cocoa – compensated the loss.

Figure 3 shows with more detail the per cent variation in SL(k) values between the subperiods 1975–2007/1998–2007 and 2008–2015. Products that experienced a higher average reduction in the SL(k) values across maturities (increase in functional efficiency) are placed more to the left and those that suffered a higher average increase of the SL(k) values (decrease in functional efficiency) more to the right. In both graphs, it can be noticed that for the two periods evaluated the same group of markets increase their efficiency after 2007. Thus, in the 1975–2007 and 2008–2015 variation in Figure 3, lean hog futures market is the first in the graph because it experienced the largest average reduction in its SL values, increasing its efficiency between these two periods more than any other product, while live cattle suffered the largest efficiency reduction. More specifically, the average variation rate of the SL(k) values for the different maturities was negative for lean hog (−37.0 per cent), cocoa (−23.6 per cent), orange juice (−23.3 per cent), sugar (−21.2), wheat (−19.6 per cent), soya bean meal (−19.2 per cent) and soya bean (−7.1 per cent), which means that their efficiency increased. The variation in the efficiency of lean hog futures contracts is congruent with other research conclusions. According to Carter and Mohapatra (2008), the U.S. hog industry has undergone dramatic changes in its size, ownership structure and the way in which prices are discovered. The large increase in the efficiency of lean hog futures follows a revamping of the CME hog futures contract in 1997 which created new challenges for industry participants. Therefore, the increase in efficiency in the 2008–2015 subperiod was probably caused by an

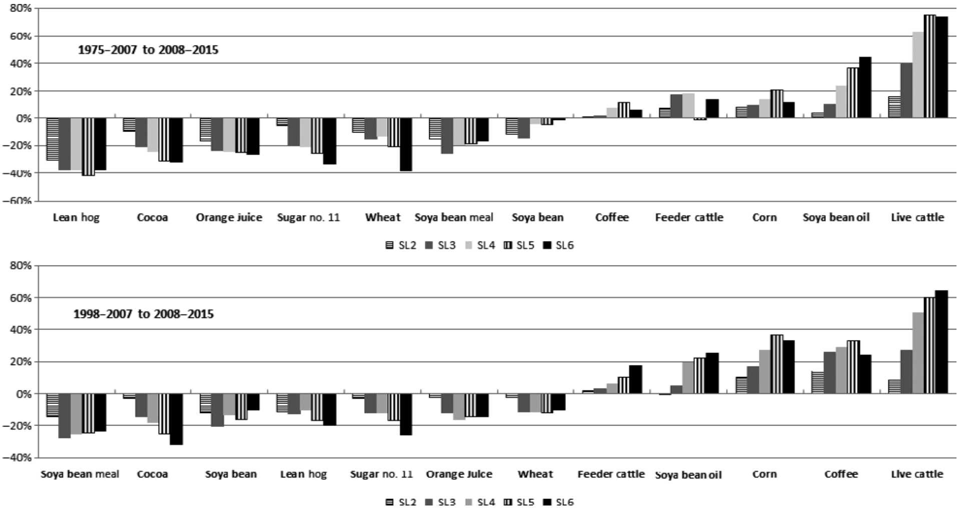

Figure 3 Per cent variation of SL (k) values from 1975–2007 to 2008–2015 and from 1998–2007 to 2008–2015.

evolution in the structure of the hog industry that gave a more prominent role to the hog futures market, successfully improving its performance.

In Figure 3, between 1975–2007 and 2008–2015 the contracts that suffered an increase in the SL(k) average value were coffee (5.5 per cent), feeder cattle (11.2 per cent), corn (12.7 per cent), soya bean oil (23.8 per cent) and live cattle (53.5 per cent). However, the average changes in SL(k) values over time in soya bean oil and live cattle hide significant variations across maturities. For instance, in the case of soya bean oil futures, the SL(2) value increased slightly over 3.3 per cent, while the SL(6) raised by almost 45 per cent. For live cattle contracts, the SL(2) increased 16 per cent, while the SL(5) raised in 75.2 per cent.

Between 1998–2007 and 2008–2015, the same group of markets increased and decreased its efficiency, but as we see in Figure 3, the order and the magnitude of SL values' variation changed. This time the increase in efficiency was not as pronounced as when we compare with the whole period before 2007, which includes all the years of less developed markets. Only with live cattle, the changes were as big as between 1975–2007 and 2008–2015, showing that in this market the loss of efficiency happened after 2007.

Therefore, the functional efficiency of futures contracts varies over time in different ways according to the type of product and the distance to maturity, reflecting not only differences in open interest but also divergences in expectations about the physical market depending on the time that has still to elapse until the end of the contract.

According to the theory of futures markets, this improvement in the functional efficiency of these contracts should be related to the increase in market liquidity in the second half of the 2000 decade, as open interest grew exponentially for almost every product with the exception of orange juice, whose efficiency went down during that same period. In any case, this assertion requires further research before drawing conclusions about the determinants of functional efficiency in agricultural futures markets.

However, there are other more basic factors that should be taken into account when explaining the evolution of SL values. First, as was explained before, the SL index is a ratio with a proxy for inevitable social loss in the denominator. Following Stein's suggestions, we have used RMSE(1) as this proxy, that is the error made when commercial participants use the futures price of the last day of the month previous to maturity as an estimate of the price when the contract expires. *Ceteris paribus*, the higher the price volatility of a contract, the higher the inevitable social loss and the lower SL(k). Consequently, part of the increase in functional efficiency might be related to an increase in the proxy for inevitable social loss.

Second, the numerator of the SL(k) index is the forecast error made k maturities from the expiration of the contract. Farming products are usually perishable and more difficult to store, and their supply is more dependent on weather conditions and other seasonal factors like plagues or pests, which are quite hard to forecast. Forecast errors and the corresponding indicator of social loss will be higher than for other less perishable commodities[8]. Even among the agricultural products considered in this article, there are specific characteristics that may explain higher or lower forecast errors leaving other things unchanged. For instance, *livestock* products should have lower forecast errors due to the nonstorability of the product and increased stability of production provided by the use of feedlots and dry lots. Therefore, the functional efficiency of their futures markets should tend to be higher than that of *grains* or *soft* products; and for the same reason glasshouse crops should have lower forecast errors than field crops.

In any case, the reduction in SL values in the 2008–2015 subperiod is another clear sign of the significant recent improvement experienced by the agricultural markets.

4. Conclusions

This article has presented a useful and simple measurement of the functional efficiency in three types of agricultural futures markets: *livestock*, *soft* products, and *grains and oilseeds* products. The SL index is shown to be a consistent indicator that can be used to quantitatively estimate social losses associated with the use of futures markets for spot price forecasting using concepts and tools related to social surplus theory.

The SL statistic computed for several agricultural futures and maturities show that this indicator can be used to compare the relative behaviour of different markets and to analyse the evolution of their functional efficiency over time. According to theory, futures prices see their capacity for prediction reduced with distance to maturity.

Empirical findings fail to support that the 2007 rapid growth in agricultural prices had noticeable consequences in the agricultural futures market efficiency. The subperiod analysis showed an important improvement in agricultural futures markets efficiency, probably associated with the growth of the different measures of activity in those markets. *Livestock* futures traded in the CME and *soft* products futures traded in the ICE were shown to be the most efficient contracts before 2007, but for 2008–2015 period *grains and oilseeds* showed an important improvement in the efficient for every period and maturity. Lean hog was the most efficient futures market probably due to the developments in the hog industry, and wheat, corn, orange juice and cocoa were the most inefficient, which is probably associated with periods of a relatively higher cost of physical storage. The successful change in the performance of lean hog futures is a good example of the fact that some

[8] Kristoufek and Vosvrda (2014) found that energy commodities are more efficient than agricultural commodities. A similar conclusion can be deduced from the comparison of the results in this paper with those in García-Verdugo and Consuegra (2013): energy futures markets have a higher functional efficiency than agricultural futures markets.

measures could be implemented to improve the efficiency in other agricultural futures markets.

A great deal of research is still needed in this area. One direction of advance would be to explain the SL and its evolution over time using the variations in futures markets variables such as open interest, trading volume and commodity price volatility. These variables were only taken into account in this article as criteria for selecting the contracts to be considered, as the agricultural futures chosen were those with higher open interest and trade volume. Another direction for this research would be the comparison between the values of the SL index associated with futures markets with the values of the indexes computed for forward contracts traded in the physical market, as was suggested by Stein (1981). Finally, a natural expansion of this research would be to apply this quantification method to other groups of commodities, such as other agricultural futures, metals and financial products.

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