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From International to Regional Commodity Price Pass-through Using Self-Driven Recurrent Networks ⋆

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Abstract. The high volatility of the agricultural and energy commodity prices in the international market is a concern due to their transmission to regional prices, increasing instability in domestic markets. This paper evaluates the performance of recurrent networks (RNN and LSTM) to predict regional prices reactions under international shock simulations. Experiments are run to soybean and corn regional prices in Argentina by considering exogenous changes of the international oil price - both agricultural commodities are inputs for biofuels' production - and also of their international prices. Results are in line with the econometric literature and consistent with the dynamic of regional prices in Argentina's markets. Thus, the RNNs could be a useful tool for timely economic policy decisions that cushion external price shocks in domestic markets.

Keywords: Recurrent Neural Networks · Regional Commodities Prices · Shock Simulations.

1 Introduction

The definition of new trade policy instruments for monitoring and stabilizing agricultural commodities prices at borders must meet specific domestic socio-economic objectives. Thus, it is essential to understand how changes in international and internal prices propagate geographically within a country. Without an accurate measurement of these effects, any quantitative analysis would be flawed, and the calibration of contingency measures distorted. For example, assuming perfect price transmission would be a risky simplification and would lead to an overestimation of the corrective power of trade policy instruments (e.g. export duties or subsidies).

The literature on price volatility focuses mainly on the cases of large exporters (e.g. United States) and more recently on the case of countries with a high food dependence on agricultural imports (e.g. Sub-Saharan African countries). The

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related economic and econometric literature evidences the inter-dependencies between the different agricultural products [22,12,19,18], and between agricultural and energy markets [23,12], explaining the dynamics of price volatility between markets. Most of these works use GARCH or MGARCH models [23,12] to assess agricultural price volatility as a function of its history. The first one captures the effects on short-term but also long-term price volatility between markets, and the second analyzes the interdependence between them (e.g. spillover effects).

While econometric methods of Vector Auto-regressive (VAR) models remain as the benchmark for price forecast, many research works are pointing to neural networks as a more precise method. Wang et al. [25] use a Back Propagation Neural Network (BPNN) to predict prices of agricultural commodities such as wheat, soy, or corn, and conclude that their predictions are more accurate than an econometric method used for comparison. Fang et al. [11] arrive at similar conclusions using a traditional Neural Network (NN).

Most of the existing research uses NN static models to predict future prices; however, they only use the state of the network in one period to predict values for the next, losing all memory of the network for the next step [17]. For time series, where each value is related to previous and next values, using static models does not properly capture the dynamics. This is particularly true for series with sudden movements or "shocks" , where predictions for static models tend to detach rapidly from real values. Conversely, a dynamic model could accurately learn from shocks and consider their information for prediction.

Recurrent Neural Networks (RNN) are a potential accurate prediction model for agricultural prices. RNNs are Neural Networks that link actual variables on their prior states, giving them a "dynamic memory" [10]. This is extremely useful to predict within a time series, where each element fed to the model is related to the previous and next values. Wang [28] uses an Echo State RNN to predict stock prices from the S&P 500, while Boyko et al. [5] use Long-Short Term Memory (LSTM), to predict upon the same database. Both papers arrive at satisfying conclusions. Moreover, Wang and Wang [26] use an Elman RNN, similar to the one used in our experiments, with a successful prediction to estimate future oil price. It is worth noting that data harmonization before applying any Machine or Deep Learning method can improve these RNN performance [27,11,25]. Furthermore, this RNN literature makes predictions based only on one single input (i.e., time lags of the same price). Nevertheless, a dynamic network could learn and forecast based also on other elements (e.g., international oil price) strongly related to the variable target.

This work implements RNN and LSTM architectures to simulate the dynamics of a closed system of prices (i.e., international prices of oil, soybean, and corn and Argentina's regional -Bahia Blanca, Rosario and Quequen - prices the same agricultural products). We focus on the training and evaluation of these models to estimate inter-dependencies between the inputs, and predict the dynamics of the regional prices. In our experiments, each international commodity is stressed under a strong shock (i.e. international price of oil), and the evolution of the regional prices on each recurrent model is evaluated as a self-driven dynamic. Recurrent models' results show good performance compared to econometric analysis, validating the use of the RNN and LSTM as a realistic engine for this application.

The paper is organized as follows. The next section states the problem, depicts the recurrent models, and details the training procedure. Experiments and analysis are detailed in section 3. Section 4 concludes the paper and propose future works.

2 Commodities Prices Prediction Models

2.1 Problem Formulation

The prediction model, represented by the R function, works with temporal series corresponding to commodities prices. We define three kinds of price series:

- $\mathbf{e}^{(t)}$ an exogenous price sequence dependent to $\mathbf{i}^{(t)}$.
- $\mathbf{i}^{(t)}$ a price sequence that it is related with $\mathbf{e}^{(t)}$.
- $\mathbf{r}^{(t)}$ a price sequence dependent to $\mathbf{i}^{(t)}$ and $\mathbf{e}^{(t)}$.

were (t) indicates the value of the price at time t. In our experiments, $\mathbf{e}^{(t)}$ is the international price of oil. The sequences $\mathbf{i}^{(t)}$ are international prices of agricultural commodities associated with bio-diesel (soybean) and bio-ethanol (corn). Because these bio-fuels (partially) replace gasoline, we can state that $\mathbf{e}^{(t)}$ and $\mathbf{i}^{(t)}$ are interdependent variables. Finally, $\mathbf{r}^{(t)}$ corresponds to agricultural commodities prices in different regions of Argentina. The dynamic of these prices involves local factors, and (what we expect to prove) external ones such as the $\mathbf{i}^{(t)}$ sequences.

The R model, at each time step (t), estimates a future value of the commodities prices based on the present state of the prices, and the previous values (memory).

The model, which simulates the behavior of the closed price system, could capture variables' inter-dependencies from the data at the learning process. This dynamic can be evaluated using *shocks*. A shock is an abrupt change in the price of one of the products in the system that could affect other products' prices. For instance, we are interested in evaluating prices' inter-dependence when applying an oil price shock. This kind of behavior happens in real life, due to political changes, wars, pandemics, and more lastly, environmental concerns.

We choose the RNN model to learn the dynamics of the closed system and predict the stationary values after the shock. Static models could not produce this kind of results as it is needed a system that receives as inputs their precedent outputs.

Modern RNN architectures introduce several improvements overcoming traditional training problems. Long-Short Term Memory model [14] (LSTM) is one of the most successful networks widely employed on several applications, such as natural language processing. LSTM deals with long-term dependencies incorporating gates to the recurrent cell.

This work implements recurrent neural networks with both RNN-Elman and LSTM cells with a forget gate. Also, we deploy a stacked RNN and LSTM network [30]. In practice, an easy way to increase the depth of the recurrent network is to stack the cells into L layers. This architecture has proved to improve efficiency and performance in problems like vehicle-to-vehicle communication [8] and French-English translation [24].

The next subsection introduces the RNN models.

2.2 Recurrent Neural Network Architecture

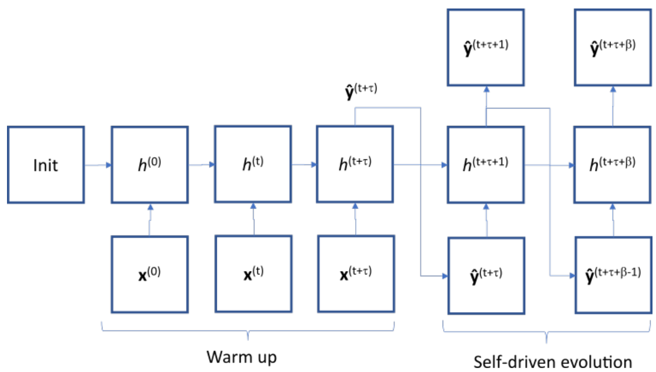

Fig. 1. System architecture and evolution.

Temporal series denoted as $(\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, ..., \mathbf{x}^{(T)})$ are usually the inputs of RNN models. In our case, $\mathbf{x}^{(t)}$ is a vector containing the commodity prices at week t including prices data from the three series $(\mathbf{e}^{(t)}, \mathbf{i}^{(t)}, \mathbf{r}^{(t)})$. Equivalently, the target sequences corresponding to the expected commodity prices is stated as $(\mathbf{y}^{(1)}, \mathbf{y}^{(2)}, ..., \mathbf{y}^{(T)})$. The predictions produced by the recurrent model are denoted as $\hat{\mathbf{y}}^{(t)}$.

The forward pass of a simple recurrent network model [17] introduces $h^{(t)}$, the hidden state of the network at time t and is defined by two equations:

$$\mathbf{h}^{(t)} = \sigma(W^{hx}\mathbf{x}^{(t)} + W^{hh}h^{(t-1)} + b_h) \tag{1}$$
$$\hat{\mathbf{y}}^{(t)} = \sigma(W^{yh}h^{(t)} + b_y) \tag{2}$$

Eq. 1 obtains $h^{(t)}$ as the combination of the input $\mathbf{x}^{(t)}$ at time t and $h^{(t-1)}$, which corresponds to the hidden previous state. These recurrent connections are what give the model memory [10]. We express the estimation of target $\mathbf{y}$ of equations 1 and 2 at time t as a dependent function R with internal parameters $\{W^{hx}, W^{hh}, W^{yh}, b_h\}$:

$$\hat{\mathbf{y}}^{(t)} = R(\mathbf{x}^{(t)}|h = h^{(t-1)}) \tag{3}$$

Fig. 1 depicts the architecture and introduces the dynamic of the proposed model. In general the internal states $\mathbf{h}^{(0)}$ at time $t = 0$ initiate with random values. Following Eq. 2, this internal states updates their values using the inputs from the temporal series, and the precedent states. Using properly trained parameters $\{W^{hx}, W^{hh}, W^{yh}, b_h\}$ the recurrent system follows the dynamic of the input sequence after some time steps. We denominate this step as *warm-up* phase, where a fixed number of time steps from a temporal series of inputs $(\mathbf{x}^{(0)}, \mathbf{x}^{(1)}, ..., \mathbf{x}^{(\tau)})$ feeds the model.

Then, in the second phase referred as *self-driven*, the input of the model at time $t + \tau + 1$ is now the model output at the previous time step $\mathbf{y}^{(t-1)}$:

$$\hat{\mathbf{y}}^{(t)} = R(\hat{\mathbf{y}}^{(t-1)} | h = h^{(t-1)})_{t>\tau} \tag{4}$$

It means that the dynamic of the model is disentangled from the input time series $\mathbf{x}^{(t)}$. Thus, their evolution only depends on the internal states values at the *warm-up* phase (memory) without any kind of input from outside the system. The *self-driven* phase should have a behavior as close as possible to the real system for at least β time steps. During this phase, the model is considered a closed system.

2.3 *Self-driven* training procedure

In order to train the recurrent neural network to follow a dynamic after international prices shock, we consider a partially closed model. This mean that the system is not completely closed and will have an external input during the *self-driven* phase. This input is the shocked commodity price.

The training follows a mini-sequences batch procedure. We split the training dataset into mini-sequences of τ length $(\mathbf{x}^{(t)}, ..., \mathbf{x}^{(t+\tau-1)})$, referred as $\mathbf{X}^{(t,\tau)}$. The target $\mathbf{Y}^{(t,\beta)}$ is also a sequence that consists of the price values of interest from $\tau + 1$ to β: $(\mathbf{x}^{(t+\tau+1)}, ..., \mathbf{x}^{(t+\tau+\beta)})$. They are the "future" prices that the model should predict within the *self-driven* phase.

More precisely, the inputs always correspond to all the agricultural prices $\mathbf{x}^{(t)} = (\mathbf{e}^{(t)}, \mathbf{i}^{(t)}, \mathbf{r}^{(t)})$, while outputs exclude the variable receiving the shock. For example, if the shock is applied on the international oil price $\mathbf{e}^{(t)}$, the output target only predicts the future value of $\mathbf{i}^{(t)}$ and $\mathbf{r}^{(t)}$: $\hat{\mathbf{y}}^{(t)} = (\hat{\mathbf{i}}^{(t)}, \hat{\mathbf{r}}^{(t)})$.

$$\hat{\mathbf{y}}^{(t)} = R((\mathbf{e}^{(t)}, \mathbf{i}^{(t)}, \mathbf{r}^{(t)}) | h = h^{(t-1)})_{t \leq \tau} \tag{5}$$

Similar to equation 4, after the *warm-up* phase, the next β time steps the output target $\hat{\mathbf{y}}$ becomes the input of the system, concatenated with the shocked variable ($\mathbf{e}^{(t)}$ for our example):

$$\hat{\mathbf{y}}^{(t)} = R((\mathbf{e}^{(t)}, \hat{\mathbf{y}}^{(t-1)}) | h = h^{(t-1)})_{t>\tau} \tag{6}$$

It generates the output sequence $\hat{\mathbf{Y}}^{(t+\tau+1, t+\tau+\beta)} = (\hat{\mathbf{y}}^{(t+\tau+1)}, ..., \hat{\mathbf{y}}^{(t+\tau+\beta)})$.

The model R seeks to predict the future value of the prices within $\mathbf{y}$. It is for that reason that the target shifts the input by one time step. The loss function computes the error made by R predicting these future values. Then, during the training process the internal parameters of the neural network are adjusted to minimize this error. Formally, the RNN loss function is defined as a mean squared error between the desired output $\mathbf{Y}$ and the estimated sequence sequence $\hat{\mathbf{Y}}$:

$$\mathcal{L} = \sum_{\beta} \frac{1}{\beta} ||\hat{\mathbf{Y}} - \mathbf{Y}|| \tag{7}$$

3 Experiments

3.1 Data description and econometric tests

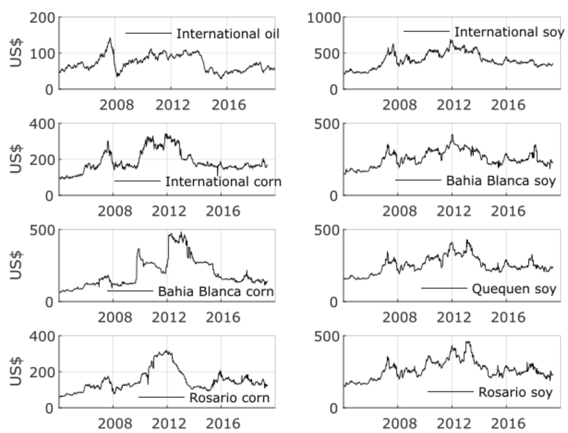

Fig. 2. International and Regional Commodities Prices data series from 2005 to 2019.

We have built a database of weekly prices in US dollars between January 2005 and August 2019, leading to a sample of 772 observations for each price.

Prices considered in the database are: Soybean and corn prices per ton in three regional markets in Argentina (Bahia Blanca - BB, Rosario - Ros, Quequén, QQ, the latter only for soybean) from GRANAR[2]; Soybean and corn international prices per ton from FAOSTAT[1]; Oil international price per barrel from the Western Texas Intermediate, WTI.

Before testing the RNN models, we have analysed the data in order to evaluate the presence of a stable long-term relationship between regional, international prices of each agricultural commodity and the international price of oil.

From an econometric standpoint, the relationship between oil and agricultural prices has been extensively studied in the literature. [7], [4], [13] and [20] are some of the first works that try to study the long run relationship between the prices of these commodities. Even though, [20] follows a panel data approach, [7], [4] and [13] tackle this issue from a time series perpective. In this sense, they perform unit root tests such as the Augmented Dickey-Fuller (ADF), the Phillips-Perron (PP) and the Kwiatkoswski-Phillips-Schmidt-Shin (KPSS) to verify if the price series of both oil and grains are first order integrated processes or I(1). Since their results verify such assumptions, they later perform cointegration test like the Johanssen approach proposed by [16]. Additionally, [7] and [13] use a two step procedure based on dynamic ordinary least squares (DOLS) and the Engle-Granger approach.

Even though the aforementioned papers are able to successfully establish a long run relationship between these prices, their analysis ignores the potential effects of structural breaks in the data. Specifically, traditional unit root tests may fail to perform in the presence of such phenomena since they may induce a bias that ultimately reduces the ability to reject a false unit root null hypothesis. For this reason, the recent literature ([6], [21], [15], [29] and [3]) use different unit root test that are able to overcome these difficulties.

Since this paper considers a time frame from 2005 to 2019, the question of whether there are structural breaks in the data is of utmost importance. For this reason, we have performed both the traditional unit root testing procedures as well as an additional one which is able to account for structural breaks. Following [9], we have performed a Breakeven Augmented Dickey Fuller test. The p-values corresponding to such test can be viewed in table 2 in the Annexes. As it can be appreciated, notwithstanding structural breaks, results indicate that all variables considered in the analysis are first order integrated processes.

Given the results, we later follow the Johansen's approach for an appropriate cointegration analysis. Tables 3 and 4 in the Annexes show that there is evidence of up to 3 cointegration relations between international oil prices, the U.S. soybean price and the Argentine soybean prices of Bahia Blanca, Quequen and Rosario. Additionally, such relationships where further confirmed by using a DOLS approach. On the contrary, tables 5 and 6 indicate that there are no cointegration relation between international oil prices, U.S corn prices and Argentine corn prices.

For the specific case of Soybean and Oil prices a 5 lag VECM was estimated. [5] Table 7 shows the Impulse Response functions generated through this estimation. Results show that Argentine Soybean prices tend to have a mild negative reaction to innovational shocks in international oil prices. However, such reaction seems to persist overtime. On the other hand, local soybean prices have a positive and persistent reaction to innovations in the price of U.S. Soybean. Lastly, responses to shocks of Soybean prices of Bahia Blanca are not significant.

In contrast, since there is not compelling evidence towards cointegration when it comes to Corn prices, we followed a VAR in difference approach.[6] Conse-

[5] The order of the VECM was selected following standard Lag-exclusion tests.

[6] In other words, we performed a first order differentiation so as to achieve stationarity.

quently, a 4 lag VAR was estimated.[7] Table 8 provides the impulse response functions for this model. Argentine Corn prices seem to have a short run positive reaction to innovations in the U.S. Corn prices. On the contrary, responses to a one time change in oil prices have little to no impact both in the short and long run.

These econometric estimations provide a reference for regional price behaviors under the recurrent network architectures.

3.2 Hyperparameters selection

Four recurrent architectures are implemented: RNN-1c, RNN-2c, LSTM-1c and LSTM-2c. Two of them consist of a single RNN and an LSTM cell. The hidden states h for RNN and (h, c) for LSTM, have H hidden units. The other architectures stack a second recurrent cell to the network with the same number of hidden units H.

We run a K-fold cross validation training, with $K = 5$, using the following set of values for $H = [4, 8, 12, 16, 20, 24, 28, 32]$. Moreover, the training is controlled by τ (*warm-up*) and β (*self-driven*) variables. Thus, the set of values for each variable are $\tau = [6, 7, 8, 9, 10]$ and $\beta = [1, 2, 3, 4]$. Note that $\beta = 1$ corresponds to a classical single prediction of the $t + 1$ output value, while $\beta > 1$ applies the loss function of eq. 7 to a sequence of targets.

Each K-fold is evaluated by two means squared error indices on the target prices of the validation split: a $MSE^{(t+1)}$ prediction, and a $MSE^{(t+N)}$ prediction. Let be $\mathbf{x}^{(t)}$ the model input, $MSE^{(t+1)}$ is computed by the mean squared error between $\hat{y}^{(t)}$ and $\mathbf{x}^{(t+1)}$. $MSE^{(t+N)}$ is obtained by using eq. 4 for a *self-driven* estimation for N steps. Then, the error is computed between prediction $\hat{y}^{(t+N-1)}$ and $\mathbf{x}^{(t+N)}$, and measures how well the recurrent model adjusts the self-driven dynamic after N steps to the real values. In this work, we fix $N = 4$ which means a month of self-driven evolution. We employ an SGD optimizer with an initial learning rate of 10^{-2}. After 20 epochs, the learning rate is reduced by half.

Table 1 shows the best results of each architecture sorted by the $MSE^{(t+N)}$ index. As can be seen, recurrent cells with a high number of hidden units H get the lowest errors. In the case of τ, *warm-up* phase seems more important for RNN cells. LSTM cells incorporate additional gates, then, this is a normal conclusion.

[7] We followed the Final Prediction Error criteria to choose the order of the VAR.

Architecture	H	τ	β	$MSE^{(t+1)}$	$MSE^{(t+N)}$
RNN-1c	32	10	2	0.159±0.093	0.195±0.156
RNN-2c	32	10	4	0.426±0.182	0.207±0.156
LSTM-1c	32	8	2	0.124±0.083	0.247±0.135
LSTM-2c	32	6	1	0.196±0.182	0.288±0.214

Table 1. Hyperparameters with the best results of the K-Fold Cross Validation.

This is expected for models like LSTM having several gates to remember/forget input data. Increasing τ also increases the temporal drift of the system itself. In the case of β parameter, the best results for RNN are obtained using values greater than one. On the other hand, LSTM prefers lower values of β.

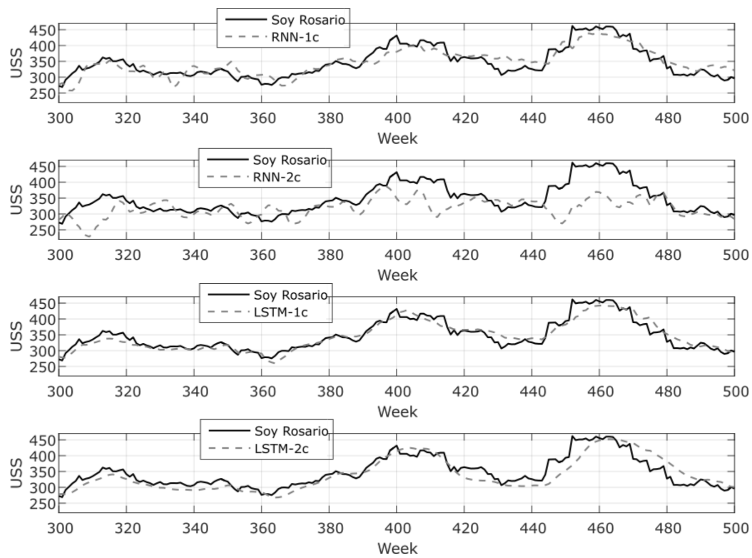

Fig. 3. System architecture and evolution.

Fig. 3 samples the $t+1$ predictions of the four models on a portion of the soybean times series prices from Rosario port. We can appreciate different behaviors for each model. RNN-1c model predicts the series values with a low error but a rapid dynamic. RNN-2c, on the other hand, seems to have a sinusoidal dynamic near the series values, but sometimes the error is high, which is consistent with the high value of their $MSE^{(t+1)}$ index on table 1. LSTM-1c and LSTM-2c predict accurately the average of the series values but have a very low dynamic. This smoothing effect is more remarkable on the LSTM-2c predictions.

3.3 International shock simulation

The experiments seek to validate the self-driven evolution of the recurrent networks when a permanent exogenous change (an increase of 100 US$) is introduced in each of international prices (own commodity and oil).

The tests are conducted as follows. For example, to test soybean exogenous change shock, we train the four models with all the commodities prices as inputs and a target that does not predict international soybean. Thus, we split the data sequences into temporal frames of $T = 35$ weeks. The first $\tau = 20$ weeks are employed as *warm-up*, and at $t = 20$, the value of the international soybean

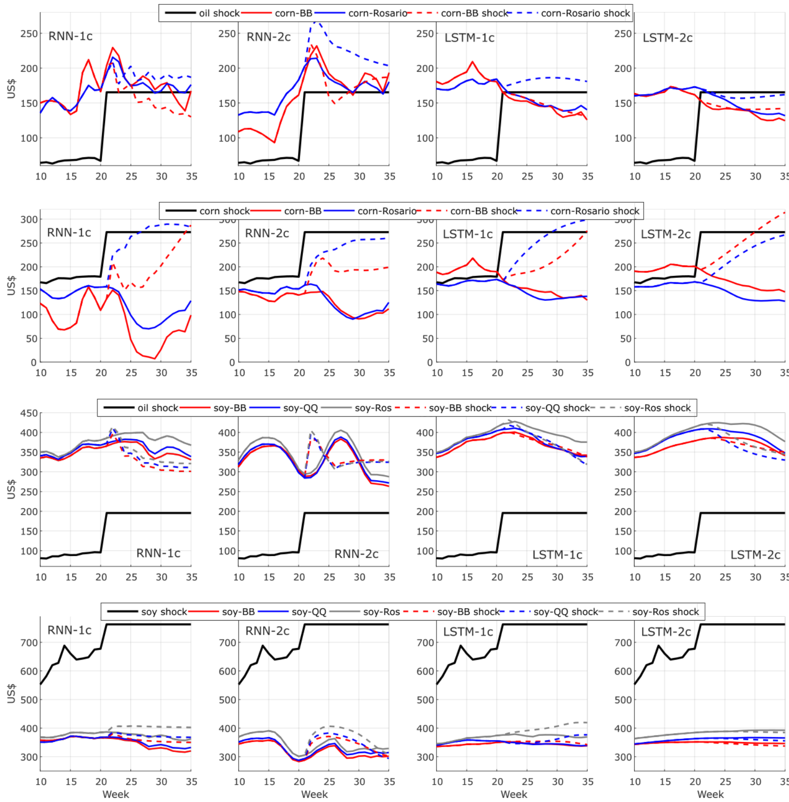

Fig. 4. Shock prediction results.

price is increased by 100 US$, keeping this value until the end of the test. At this point, the system uses both the new value of the international soybean price and the self-prediction of other prices as input.

For example, Fig. 4 depicts in black line the international variable employed to perform the shock and in colors (red, blue, green) the evolution of the regional prices. In solid lines, the picture draws the regional prices without the shock, and the dashed lines depict the self-driven dynamic of the system. The chosen timeframes in Fig. 4 are in line with the regional prices behaviors in the Impulse-Response function based on econometric models considered as reference. It is worth mentioning that we need to train a different model each time we change the international price to perform the shock.

According to the results in Fig. 4, when considering an exogenous increase of the international oil price, soybean prices in regional markets of Argentina are immediately impacted, but the reaction depends on the model considered, e.g. the RNN-2c displays greater volatility. Nevertheless, the decreasing convergence paths of all models (consistent with econometric estimations) lead to the same new stationary state.

While the regional soybean prices in Argentina recover stability near to the path without shock, the regional corn prices show greater volatility facing the same exogenous shock. Except for the LSTM-2c, regional corn prices display a great difficulty to recover the path without shock, and Bahia Blanca and Rosario corn markets show different behaviors between them and across models. Their different paths of convergence increase the price-gap between regions (supported by the econometric estimations).

Finally, when assuming an exogenous increase in the international price of their agricultural commodity, regional markets prices display greater positive reactions (particularly for corn) and convergence towards higher values compared to their values without shock. Regional soybean prices converge to a higher price in the new stationary state, except under the LSTM-2c, which brings the price back to the path without shock. Reactions of regional corn prices to their international price increase are greater than in the case of soybean and tend to converge close to the new level of the international price of corn.

The difference between the reactions of soybean and corn regional prices to their own international prices is due to Argentina's soybean and corn markets particularities. These results are in line with the role of Argentina as a big soybean producer in the international market, so it is considered as a price maker. Conversely, in the international corn market Argentina is a relatively small player being a price-taker, so a change in the international price of corn is strongly transmitted to regional prices.

4 Conclusions

In this paper, we have trained four recurrent networks to forecast the reaction of regional commodity prices when an exogenous variable (i.e., an international price) is shocked. Results have been validated since they are in line with estimations from econometric auto-regressive models. The self-driven dynamic of recurrent networks has been demonstrated to be consistent with the behavior of Argentina's soybean and corn markets. To reduce regional price volatility, RNNs become a new tool to predict domestic prices' reactions to international changes and provide relevant insights for policy-makers decisions.

Further works should consider more complex recurrent networks, including other variables related to these agricultural and energy prices (e.g., bio-ethanol and bio-diesel prices) and also other regional variables that condition regional price path-through (e.g., transport costs).

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5 Annex

Table 2. P-values from unit root test for all variables-Levels and first difference

	Level			First Difference		
	ADF	PP	ADF with Breakeven	ADF	PP	ADF with Breakeven
Oil	0.27	0.13	0.21	0.00	0.00	0.00
Soybean-USA	0.18	0.18	0.52	0.00	0.00	0.00
Soybean-Bahia Blanca	0.17*	0.23 *	0.20	0.00	0.00	0.00
Soybean-Rosario	0.10	0.11	0.56	0.00	0.00	0.00
Soybean-Quequen	0.12	0.13	0.46	0.00	0.00	0.00
Corn-USA	0.12	0.17	0.81	0.00	0.00	0.00
Corn- Bahia Blanca	0.22	0.22	0.90	0.00	0.00	0.00
Corn- Rosario	0.16	0.17	0.81	0.00	0.00	0.00

The null hypothesis for all test was that the series has unit root.
*A trend was added in the specification of the test.

Table 3. Johanssen Test for Cointegration between Oil prices, Soybean-USA, Soybean-Bahia Blanca, Soybean-Quequen and Soybean-Rosario-Trace

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.095647	148.7163	69.81889	0.0000
At most 1 *	0.046889	71.70606	47.85613	0.0001
At most 2 *	0.027860	34.91937	29.79707	0.0118
At most 3	0.010779	13.27600	15.49471	0.1051
At most 4 *	0.006473	4.974404	3.841465	0.0257

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values
A VECM with 5 lags was estimated to perform this test

Table 4. Johanssen Test for Cointegration between Oil prices, Soybean-USA, Soybean-Bahia Blanca, Soybean-Quequen and Soybean-Rosario-Eigenvalue

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.095647	77.01028	33.87687	0.0000
At most 1 *	0.046889	36.78669	27.58434	0.0025
At most 2 *	0.027860	21.64338	21.13162	0.0424
At most 3	0.010779	8.301591	14.26460	0.3489
At most 4 *	0.006473	4.974404	3.841465	0.0257

Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

A VECM with 5 lags was estimated to perform this test

Table 5. Johanssen Test for Cointegration between Oil prices, Corn-USA, Corn-Bahia Blanca and Corn-Rosario- Trace

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.030020	46.19916	47.85613	0.0710
At most 1	0.012702	22.82100	29.79707	0.2550
At most 2	0.009599	13.01601	15.49471	0.1142
At most 3 *	0.007298	5.618261	3.841465	0.0178

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

A VECM with 4 lags was estimated to perform this test

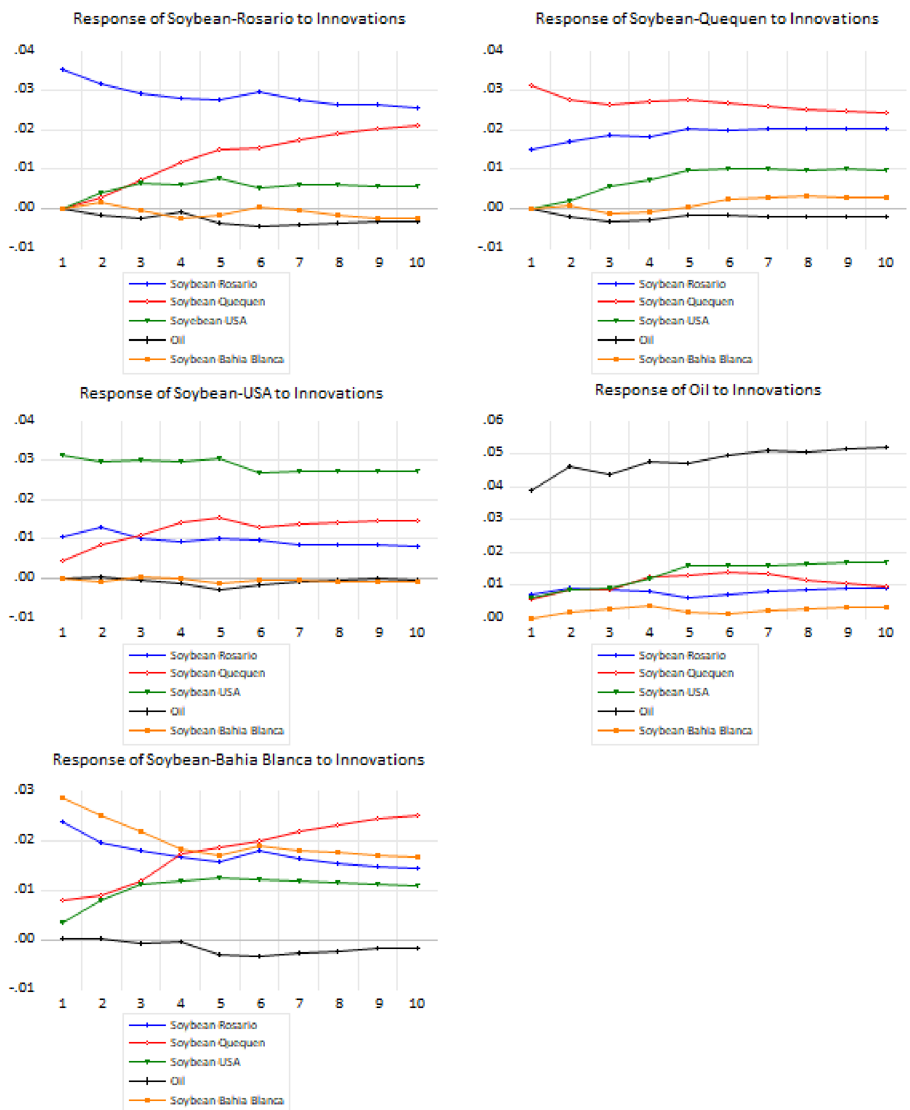
Table 6. Johanssen Test for Cointegration between Oil prices, Corn-USA, Corn-Bahia Blanca and Corn-Rosario- Eigenvalue

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.030020	23.37816	27.58434	0.1579
At most 1	0.012702	9.804997	21.13162	0.7627
At most 2	0.009599	7.397746	14.26460	0.4432
At most 3 *	0.007298	5.618261	3.841465	0.0178

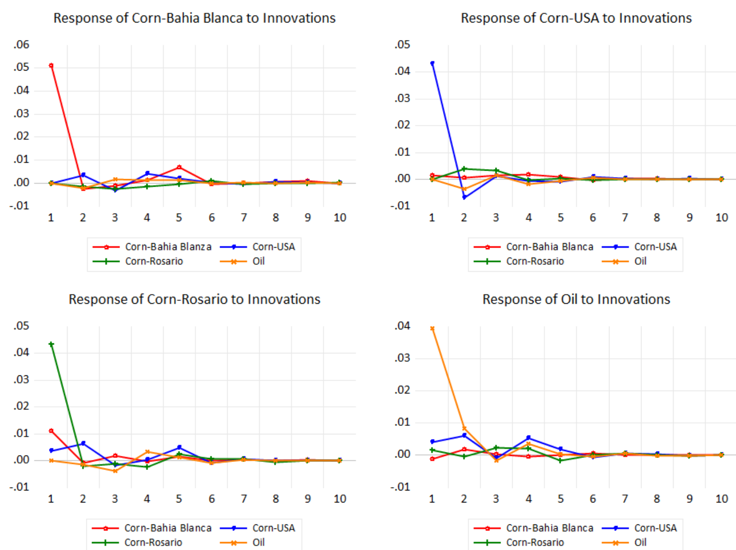
Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values
A VECM with 4 lags was estimated to perform this test

Table 7. Impulse response functions of the VECM for Soybean and Oil Prices



The impulse response functions provided where the result of a VECM estimation with 5 lags. Cholesky decomposition method was used.

Table 8. Impulse response functions of the VAR for Corn and Oil Prices



The impulse response functions provided where the result of a VAR estimation with 4 lags. Cholesky decomposition method was used.

Table 9. Output estimation for a 4 lag VAR in difference- Oil prices, Argentine and U.S. corn prices

	Corn-Bahia Blanca	Corn-USA	Corn-Rosario	Oil
Corn-Bahia Blanca(-1)	−0.049734	−0.005439	−0.013203	0.041909
	(0.03724)	(0.03123)	(0.03269)	(0.02896)
	[-1.33559]	[-0.17418]	[-0.40387]	[1.44730]
Corn-Bahia Blanca(-2)	−0.007916	0.019804	0.040087	−0.013059
	(0.03722)	(0.03121)	(0.03268)	(0.02894)
	[-0.21269]	[0.63448]	[1.22680]	[-0.45120]
Corn-Bahia Blanca(-3)	0.028498	0.031768	0.013974	−0.014518
	(0.03707)	(0.03108)	(0.03254)	(0.02882)
	[0.76883]	[1.02198]	[0.42942]	[-0.50369]
Corn-Bahia Blanca(-4)	0.142204	0.020360	0.008832	0.002734
	(0.03698)	(0.03101)	(0.03247)	(0.02876)
	[3.84518]	[0.65650]	[0.27203]	[0.09507]
Corn-USA(-1)	0.090591	−0.160724	0.153632	0.122152
	(0.04385)	(0.03678)	(0.03850)	(0.03410)
	[2.06578]	[-4.37042]	[3.99051]	[3.58213]
Corn-USA(-2)	−0.041323	−0.011095	0.008257	−0.030047
	(0.04524)	(0.03794)	(0.03972)	(0.03518)
	[-0.91332]	[-0.29242]	[0.20788]	[-0.85403]
Corn-USA(-3)	0.085522	−0.029218	0.008481	0.116797
	(0.04508)	(0.03781)	(0.03958)	(0.03506)
	[1.89691]	[-0.77280]	[0.21428]	[3.33151]
Corn-USA(-4)	0.074425	−0.013683	0.111594	0.017445
	(0.04467)	(0.03746)	(0.03922)	(0.03474)
	[1.66601]	[-0.36525]	[2.84544]	[0.50220]
Corn-Rosario(-1)	−0.029280	0.093583	−0.044147	−0.015067
	(0.04278)	(0.03588)	(0.03756)	(0.03327)
	[-0.68444]	[2.60857]	[-1.17548]	[-0.45292]
Corn-Rosario(-2)	−0.073137	0.089494	−0.039108	0.047010
	(0.04271)	(0.03582)	(0.03750)	(0.03321)
	[-1.71239]	[2.49864]	[-1.04298]	[1.41546]
Corn-Rosario(-3)	−0.041473	0.020818	−0.073958	0.029108
	(0.04291)	(0.03599)	(0.03767)	(0.03337)
	[-0.96645]	[0.57849]	[-1.96311]	[0.87231]
Corn-Rosario(-4)	−0.024197	0.024966	0.055063	−0.048385
	(0.04255)	(0.03568)	(0.03735)	(0.03309)
	[-0.56870]	[0.69970]	[1.47409]	[-1.46240]
Oil(-1)	−0.050457	−0.094393	−0.039450	0.209716
	(0.04713)	(0.03953)	(0.04138)	(0.03665)
	[-1.07050]	[-2.38807]	[-0.95336]	[5.72184]
Oil(-2)	0.060901	0.044062	−0.075754	−0.074614
	(0.04773)	(0.04002)	(0.04190)	(0.03711)
	[1.27604]	[1.10088]	[-1.80798]	[-2.01049]
Oil(-3)	0.010265	−0.039755	0.091957	0.106661
	(0.04793)	(0.04019)	(0.04208)	(0.03727)
	[0.21418]	[-0.98912]	[2.18551]	[2.86196]
Oil(-4)	0.053707	−0.006631	0.012808	−0.013941
	(0.04660)	(0.03908)	(0.04091)	(0.03623)
	[1.15262]	[-0.16970]	[0.31309]	[-0.38476]
Constant	0.000886	0.000683	0.000800	$-5.94E-05$
	(0.00185)	(0.00155)	(0.00162)	(0.00144)
	[0.47919]	[0.44059]	[0.49303]	[-0.04134]

Standard errors in ( ) & t-statistics in [ ]