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Animal Diseases and Global Markets: How did the African Swine Fever outbreak in China impact Brazilian soybean price returns?

by Luis A. C. Schmidt and Leaonardo Bornacki de Mattos

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Animal diseases and global markets: how did the African Swine Fever outbreak in China impact Brazilian soybean price returns?

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Abstract

African Swine Fever (ASF) is a highly contagious and generalized disease that affects pigs and its relatives from the suidae family. The disease's mortality is usually close to the 100% rate and, since there is no vaccine available in the market, its control depends on quarantine enforcement and stamping out policies. China lost almost 30% of its pig herd to African Swine Fever and, which led to spillovers in other sectors. For example, since pigs are fed with soybeans by-products, imports of this commodity fell significantly. This paper investigates how ASF impacted soybean price returns in Brazil, world's leading soybean exporter. With the use of ARMA and GARCH models, we find that when the outbreaks of ASF in China reached its peak, soybean price returns in Paraná suffered a negative impact.

Keywords: Animal Health Economics. African Swine Fever. Volatility. GARCH.

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1 Introduction

African Swine Fever (ASF) is a highly contagious and generalized disease that affects pigs and its relatives from the suidae family, such as African wild suids and European wild boars. The virus is spread through transmission cycles involving domestic and wild pigs from all ages and breeds, as well as through the bites of the soft-bodied Ornithodoros ticks. Indirect transmission through uncooked meat, vehicles, clothes and other fomites adds to the epidemiological complexity (OIE, 2020a,b).

The ASF virus (ASFV) has several strains with varying virulence profiles and is very hardy to inactivation, so currently there is no effective vaccine or medicine to prevent or to treat the disease. A common characteristic of the disease is its almost certain mortality[1], which is usually close to the 100% rate. For this reason, the control of the disease depends on quarantine enforcement and stamping out policy, which consists on mass culling of animals in infected areas (FAO, 2020).

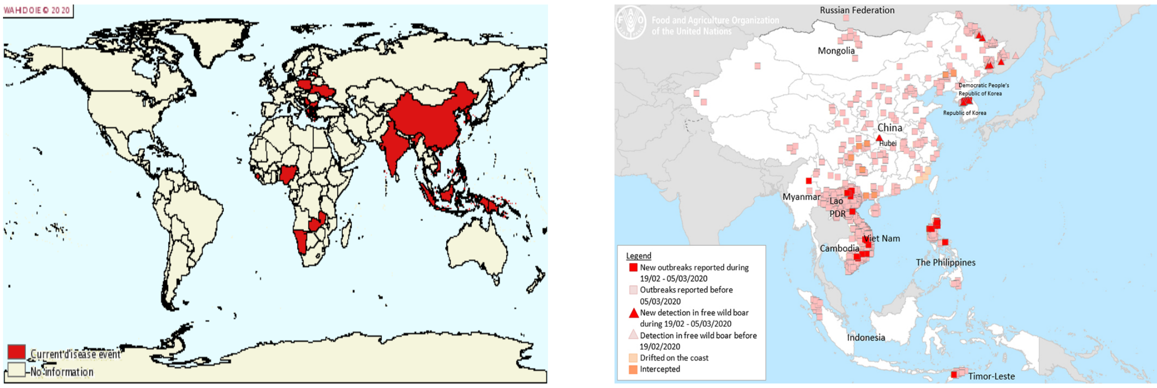
As of June 2020, ASF is present in more than 50 countries in Africa, Europe and Asia. The African continent was the first to register the disease and several incursions were reported between the 1960s and 1970s. In 2007, ASFV began to spread on eastern Europe after the first cases being reported in Georgia and, in 2014, the disease reached the European Union (OIE, 2020b).

African Swine Fever was first reported in Asia on August 2018, when the Ministry of Agriculture and Rural Affairs (MARA) of China confirmed the first outbreak in Liaoning Province. As shown in Figure 1, the disease spread throughout the country and the rest of the continent afterwards.

1.1 Economic impacts of ASF

China has the largest swine population in the world and accounted for approximately 48% of the world's pork production before the advent of the ASF epidemy in the country.

[1]Mortality rate is given by the ratio between the amount of animals deceased from the disease and the total infected animals.

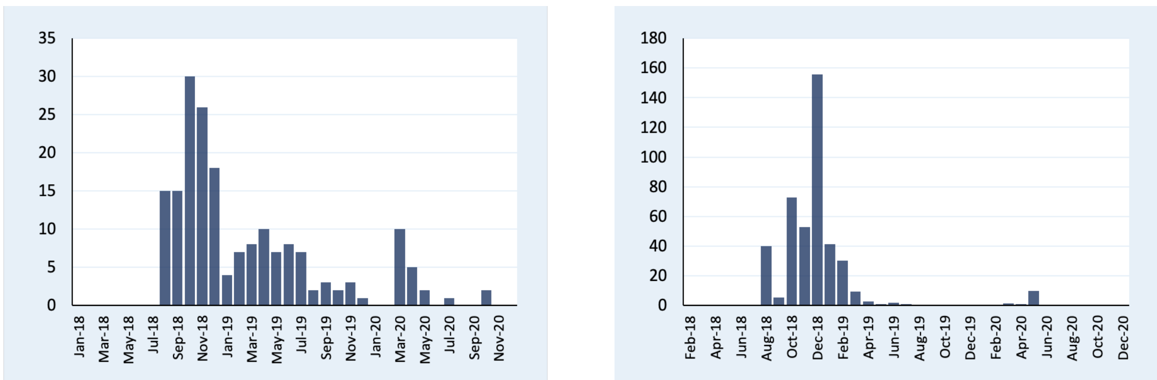


(a) ASF distribution by June, 2020.   (b) Events from August 2018 to March 2020.

Figure 1: Distribution of African Swine Fever across the world and recent events of ASF outbreaks in Asia. (WAHIS, 2020; FAO, 2020)

A important feature and source of risk is that small-scale and backyard farms with low biosecurity practices account for more than 60% of pig production in China (Wang et al., 2018).

The most direct economic impacts of severe diseases is on production and productivity. Sick animals stop producing or fattening because they might not eat, drink or move properly. Besides, notification of ASF is mandatory, so as soon as an outbreak is confirmed, the authorities are notified. As a measure of disease control, all the animals in the susceptible area are culled. Figure 2 shows the development of ASF in China. Since August 2018, 186 outbreaks were reported and more than 377,000 pigs were deceased. As a result of the disease and to control its spread, we see from Figure 3a that China lost almost 30% of its herd.



(a) Outbreaks   (b) Deaths (thousands).

Figure 2: Outbreaks of African Swine Fever in China and total deaths from the disease. Deaths from stamping out policy are included. (WAHIS, 2020)

Several economic disturbances surge because of extreme events like the epidemic of ASF. With its growing population, China is not only the largest pig producer, but also the largest pork consumer of the world. Hence, the plunge of 30% on China's pig herd has the potential to harm other sectors of the economy, both locally and globally.

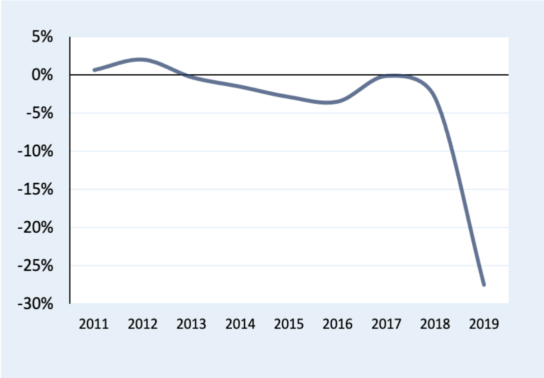
Besides pork, China is also the largest consumer and the largest importer of soybeans in the world. Pigs and soybeans are in the roots of Chinese culture and their markets are deeply connected, not only because of people's consumption, but also because pigs are fed with soybeans by-products.

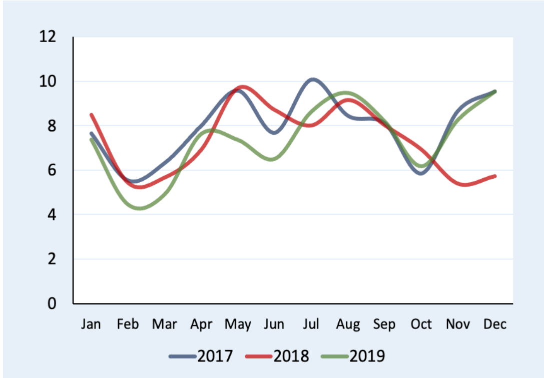
In fact, from Figure 3b, which shows China total imports of soybeans, it is clear how the pattern changed after the first months of outbreaks, specially from October 2018 on. If, on the one hand, China is the largest importer, on the other hand, Brazil is the world's leading producer and exporter of soybeans. Figure 3c and 3d show that Brazilian soybeans exports seem to have suffered with China's shock of demand: in 2019, Brazilian soybean exports to China fell 15% and did not recover until mid-2020.

There exists a vast literature about animal disease impacts, although a large part of it consists of veterinary research and more "direct" impacts, such as farm-level losses or local economic impacts. Some research with broader economic analysis commonly studies impacts of endemic or epidemic diseases on volatility of prices. The aim of this paper is to investigate the impact of an infectious disease across markets, i.e., the impacts of African Swine Fever in China on Brazilian agribusiness sector. More specifically, we will study how the stamping out policy that took place in China affected the prices of soybean in Brazil.

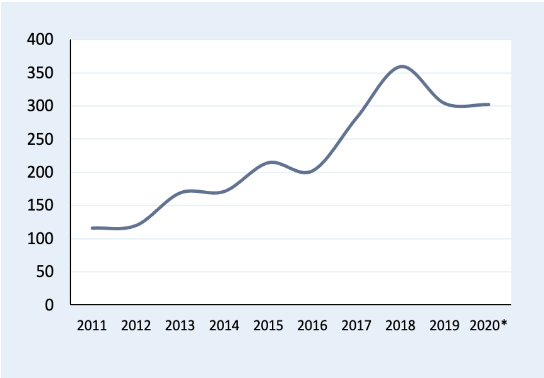
2 Methodology

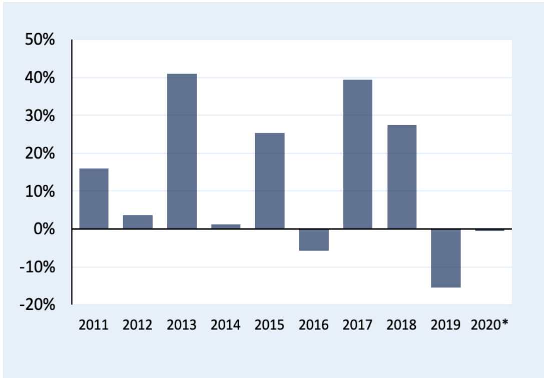
To analyse the impacts of the outbreak of ASF as described in the previous sections, we estimate a Generalized Auto-regressive Conditional Heteroskedasticity (GARCH) model.





(a) **(b)**





(c) **(d)**

Figure 3: **(a)** Growth of China's domestic swine herd. Quantity of animals measured at the end of each year. **(b)** China soybeans imports from the world (Millions of tons). **(c), (d)** Soybeans exports (HS Code 1201 Soybeans, whether or not broken) from Brazil to China (2010=100). **Source:** National Bureau of Statistics of China; General Administration of Customs of China; Brazil's Ministry of Development, Industry and Foreign Trade (MDIC). *Data up to August, 2020.

2.1 Data

To analyse behavior of the price volatility of soybean in Brazil, we will study the Cepea/Esalq[2] Soybean Price Index - Paraná State from 2016 to 2019. The Index is built in a daily frequency and refers to trades in the wholesale market, with prices net from ICMS[3] tax and term prices discounted by NPR[4]. Price information is collected through a survey with participants of the market, such as cooperatives, trading companies and brokers, distributed across five regions of the state: Paranaguá, Ponta Grossa, northern,

[2]Cepea is the economic research center at Esalq ("Luiz de Queiroz" College of Agriculture at University of São Paulo - USP)

[3]ICMS (Imposto sobre Circulação de Mercadorias e Serviços) is a brazilian tax on commerce and some services and is the main tax levied by all 26 federal states. It applies to the movement of goods, to services of transportation between several states or municipalities and to telecommunications services.

[4]NPR (Nota Promissória Rural) is a term contract where a downstream agent commits to buy a specified amount of agricultural products and the agricultural producer commits to deliver it. This promissary note can be used by the buyer party as collateral for short-term bank loans.

western and southwestern Paraná. Prices refer to export-quality soybeans in bulk and is measured in Brazilian Real per 60 kg bags.

Figure 4 shows the evolution of the index from 2016 to 2019. As expected for commodity prices, there are high fluctuations along the years. With such a pattern, it would not be correct to choose some periods and try to determine how the prices responded to specific shocks.

To have a better measure of the prices behavior and achieve higher prediction capabilities, we transform the data to soybean price returns. Returns are defined by the daily log difference of prices: $r_t = ln(p_t) - ln(p_{t-1})$, where r_t are the Soybeans Price Index returns at time t and p are the prices of export-quality soybeans at times t and $t-1$. As Graph 2 in Figure 4, returns behave similar to a stationary time series, except for the fact that the variance is not constant.

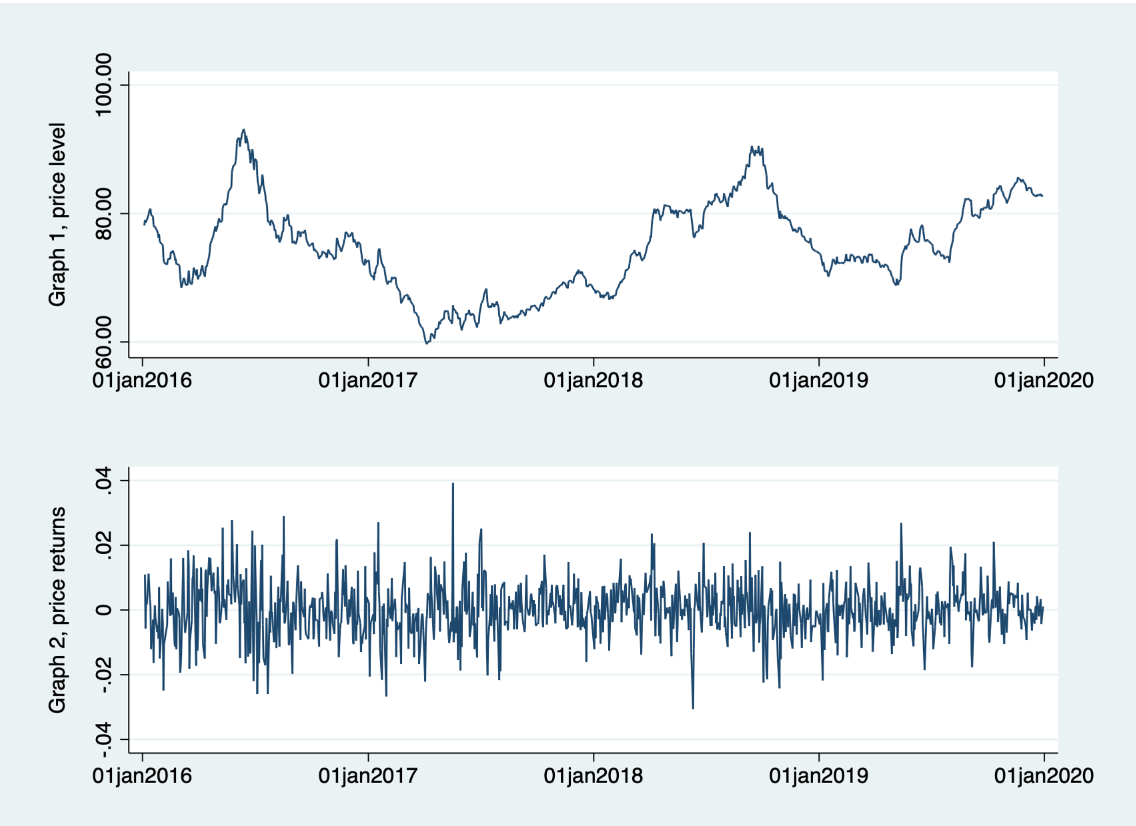


Figure 4: Soybean Price Index and Returns. Prices in R$ per 60 kg bags. (Cepea/Esalq)

To account for the African Swine Fever outbreak in China, we create a binary variable taking values of 1 in the period of the outbreak and 0 otherwise. Ministry of Agriculture and Rural Affairs (MARA) of China notified its first ASF outbreak on 3 August 2018. As shown in Figure 2a, outbreaks increased to a peak in October and gradually declined until December. Outbreaks continued to surge in all 2019, but in a lower quantity of regions and in a more stable pace.

2.2 Empirical analysis

To model the price volatility of soybeans in Paraná and test how it was impacted by ASF, we estimate a Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) model, pioneered by Bollerslev (1986). First, we estimate the mean equation as an auto-regressive moving average model. Following the Auto-Correlation Function (ACF) and the Partial ACF, as well as Akaike's criteria information, we specified an ARMA(1,2) model:

$$r_t = \phi_0 + \phi_1 r_{t-1} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \varepsilon_t, \tag{1}$$

where r_t are the Soybeans Price Index returns and ε_t are the residuals of the regression, which are used as an exogenous variable in the GARCH model. As usual, we compared the four main specifications[5] of the model. The specification GARCH(1,1) was the best fit for the variance. Our model is then defined by:

$$\begin{aligned} \varepsilon_t =& \sqrt{\sigma_t^2} u_t, \;\; u_t \sim \text{i.i.d.}(0,1) \\ &\text{and} \\ \sigma_t^2 =& \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \end{aligned} \tag{2}$$

where ε_t is the error term of the mean equation, u_t are stochastic innovations and σ_t^2 is the conditional variance. This conditional variance is described in terms of its lags and of the lagged erros of the mean equation. In the model, ε_t and σ_t^2 describes the ARCH and GARCH terms, respectively.

After the identification of the GARCH model and assuring that the problems of serial auto-correlation and conditional heteroskedasticity are succesfully adressed, the model

[5] GARCH(1,1), GARCH(1,2), GARCH(2,1) and GARCH(2,2).

will be trustful to estimate the impacts of the outbreaks of ASF in China on Brazilian soybean prices volatility. To achieve this, the dummy variable ASF defined in Section 2.1 is included in the model. Thus, the specification of interest of this research is:

$$\begin{aligned} r_t =& \phi_0 + \delta_1 ASF_t + \phi_1 r_{t-1} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \varepsilon_t \\ \varepsilon_t =& \sqrt{\sigma_t^2} u_t, \;\; u_t \sim \text{i.i.d.}(0{,}1) \\ \sigma_t^2 =& \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \end{aligned} \tag{3}$$

3 Results

Some financial series, such as stock returns, do not commonly present serial auto-correlation. However, as this behavior is present in our Soybean Price Index returns, we adjusted an ARMA(1,2) for the mean equation before modelling the variance with a GARCH model. The residuals of this specification are not auto-correlated.

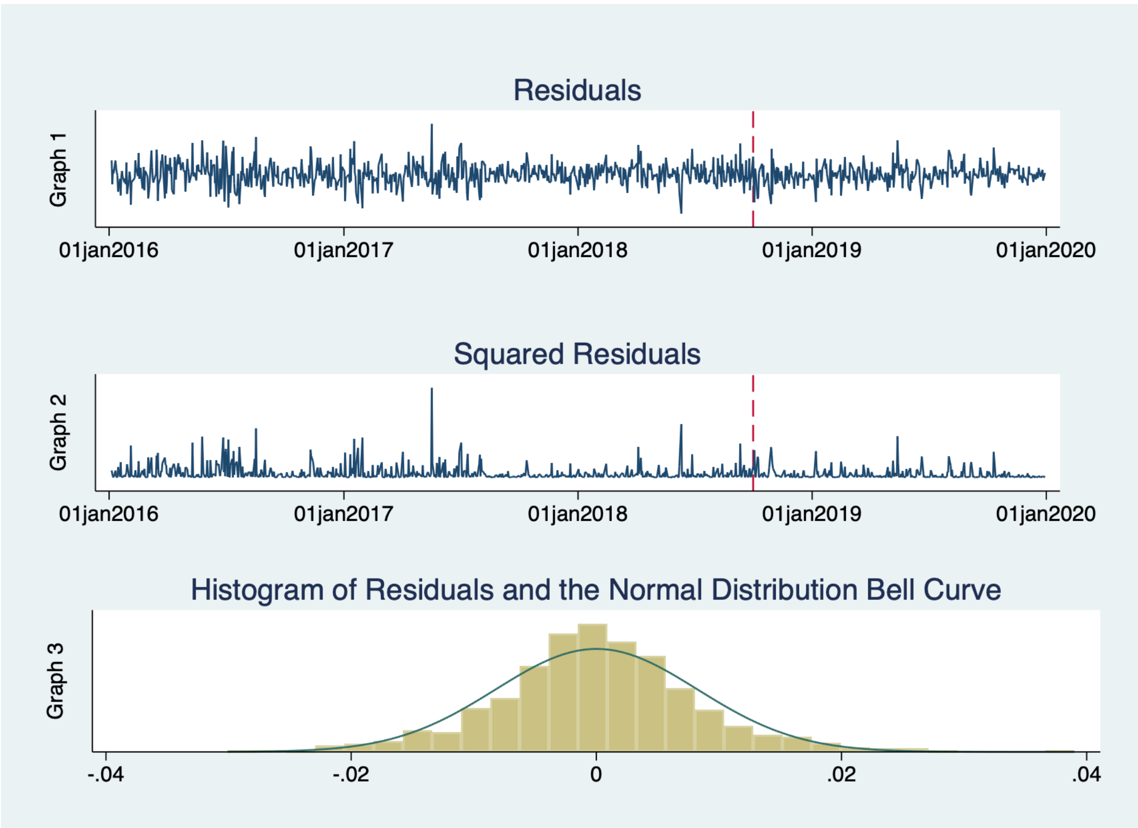


Figure 5: ARMA(1,2) model for Soybean Price Index. Dashed red line inserted on October 01, 2018. ASF outbreaks reached its peak on that month.

Graph 1 from Figure 5 shows that the residuals have a zero constant mean, but variance is not constant. In fact, we can notice several volatility clusters in the squared returns in Graph 2. This characteristic indicates that even with the disturbances being not serially auto-correlated, they are not independent and identically distributed (i.i.d.). This means that the residuals have heteroskedastic variance.

Graph 3 shows a leptokurtic distribution of the residuals, meaning that they do not follow the normal distribution. We ran the Jarque-Bera test, which confirmed the non-normality of the residuals. Information displayed in Figure 5 suggests that the series may have autoregressive conditional heteroskedasticity – or ARCH effects. To confirm this hypothesis, we use the Lagrange Multiplier (LM) test to test for autoregressive conditional heteroskedastic residuals. Results are on Table 1.

Table 1: LM test for autoregressive conditional heteroskedasticity (ARCH-LM).

Lags(p)	**Chi2**	**DF**	**Prob>chi2**
1	6.473	1	0.0110
2	9.092	2	0.0106
3	9.123	3	0.0277
4	18.486	4	0.0010
5	18.875	5	0.0020
6	27.566	6	0.0001

Source: Research results by the author.

LM test's null hypothesis is that there are no ARCH effects in the series, meaning that disturbances are homocedastic. The alternative hypothesis is that disturbances follow an ARCH(p) process. We ran the test for the first 6 lags and lags are statistically significant at the 5% confidence level. Therefore, we reject the null hypothesis and confirm that ARCH effects are present in the soybean price returns. We estimate a GARCH(1,1) model and present the results on Table 2.

All relevant coefficients are statistically significant. From the mean equation, ϕ_1, the coefficient associated with the AR(1) term, is significant at the 1% confidence level. It has a positive impact on the returns, i.e., volatility on day t is positively correlated with the volatility observed on the previous day.

Coefficients associated with the MA(2) terms are also statistically significant, but

Table 2: GARCH(1,1) estimates on Soybeans Price Index returns.

	Coefficient	**Std. Error**	**z**	**P> $\|z\|$**
Constant				
ϕ_0	0.0000328	0.0003735	0.09	0.930
Mean equation - ARMA				
ϕ_1	0.9091606	0.066553	13.66	0.000***
θ_1	-0.761982	0.0739096	-10.31	0.000***
θ_2	-0.0908991	0.0375292	-2.42	0.015**
Variance equation - GARCH				
α_0	9.39e-07	7.64e-07	1.23	0.219
α_1	0.0468913	0.0157097	2.98	0.003***
β_1	0.9402175	0.0213275	44.08	0.000***
Degrees of freedom	6.39876	1.447027		

Source: Research results by the author.
Notes: *p<0.1; **p<0.05; ***p<0.01.

they influence the returns in the opposite way: when past disturbances are positive, price returns are negative. θ_1 presents a higher impact and is significant at the 1% confidence level, whereas θ_2 impacts the returns less than θ_1 and is significant at the 5% level. This result ($\theta_1 > \theta_2$) is consistent with the model specification as they account for the MA(2) terms.

Variance equation also has significant coefficients, both at the 1% level. α_1 and β_1 are positive, meaning that price returns are positively correlated with previous day variance and previous day mean equation error. These results are in line with our initial graphical interpretation, since volatility clusters are generated by this positive correlation. The sum of α_1 and β_1 is known as the degree of volatility persistence. In our model, $\alpha_1+\beta_1 = 0,987$, which means that volatility shocks highly persistent, i.e., shocks take time to dissipate.

Now that our model is adequately specified, we include the dummy variable to account for the many ASF outbreaks that occurred after August, 2018. For the purposes of this article, we evaluate the impacts starting from October, 2018, which had the highest number of outbreaks of ASF. Results are presented on Table 3.

Despite the inclusion of a new variable, the model performed very similarly to the previous one. Coefficients from the mean and variance equations did not change much and are still highly statistically significant. The inclusion of the new variable is also

Table 3: GARCH(1,1) estimates on Soybeans Price Index returns with a dummy variable for ASF outbreaks in China (October to December 2018 = 1, otherwise = 0).

	Coefficient	**Std. Error**	**z**	**P$>|z|$**
Constant				
ϕ_0	0.0001885	0.0003447	0.55	0.585
ASF outbreaks				
δ_1	-0.0025919	0.001482	-1.75	0.080*
Mean equation - ARMA				
ϕ_1	0.8777223	0.1051879	8.34	0.000***
θ_1	-0.7345973	0.1106761	-6.64	0.000***
θ_2	-0.0863633	0.0414617	-2.08	0.037**
Variance equation - GARCH				
α_0	8.82e-07	7.35e-07	1.20	0.230
α_1	0.046159	0.0155804	2.96	0.003***
β_1	0.9416123	0.0209159	45.02	0.000***
Degrees of freedom	6.537197	1.488068		

Source: Research results by the author.
Notes: *p<0.1; **p<0.05; ***p<0.01.

significant. At the 10% confidence level, we find that when the outbreaks of ASF in China reached its peak on October, 2018, soybean price returns in Paraná suffered a negative impact.

4 Conclusion

Since August 2018, China has suffered with several outbreaks of African Swine Fever and lost almost 30% of its pig herd. With this huge negative shock, soybean imports from China dropped, since the commodity's by-products are used to fed pigs. Through a GARCH modelling, we were able to estimate a regression for the Soybean Price Index returns. We find that the returns suffered a negative shock in response to ASF outbreaks in China after it reached the peak on October, 2018.

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