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# The Reliability of Spanish and German Electricity Forward Prices. Databases and Price Discovery Process

Ángela Coronado, Francisco Climent \*  and Dolores Furió 

Departament d'Economia Financera i Actuarial, Facultat d'Economia, Universitat de València, 46022 València, Spain; angelacoronado93@gmail.com (Á.C.); m.dolores.furio@uv.es (D.F.)

\* Correspondence: f.jose.climent@uv.es; Tel.: +34-963828369

**Abstract:** Given the existence of different databases from different sources that offer information on forward electricity prices, the need to compare them arises to guarantee that research results and trading decisions based on them are not sensitive to the database used. We worked with forward electricity prices traded over the counter, closest month to maturity, covering the period from 2010 to 2016 for the Spanish over the counter (OTC) market, and from 2008 to 2016 for the German OTC market. The goal of this paper was to test whether there were significant discrepancies between the price series provided by two of the main agencies of financial information (Thomson Reuters and Bloomberg), as well as to analyze the existence of causality relationships between them, both in the long-term and in the short-term. As a first step, we obtained the data availability and the distributional characteristics of each of the price series offered by the mentioned financial information providers for the Spanish and the German electricity OTC market. Then we studied the lead-lag relationship between two price series, previously chosen as representative of those provided by Thomson Reuters and Bloomberg, to ascertain if there are any leading databases that may systematically anticipate information with respect to the others.



**Citation:** Coronado, Á.; Climent, F.; Furió, D. The Reliability of Spanish and German Electricity Forward Prices. Databases and Price Discovery Process. *Mathematics* **2021**, *9*, 623. <https://doi.org/10.3390/math9060623>

Academic Editor: Jose Manuel Brotons Martínez

Received: 25 January 2021  
Accepted: 2 March 2021  
Published: 15 March 2021

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**Keywords:** electricity; databases; price discovery

## 1. Introduction

The generalized process of liberalization of the electricity sector in Europe entailed a radical change in the setting of electricity prices, moving from a regulated price to a price that results from the interaction of supply and demand forces in a pool governed by competitive rules. This fact led to the emergence of a new type of risk for the agents participating in the electricity sector, namely, the price risk, which is defined as the risk of losses in positions arising from adverse movements in market prices. Derivatives markets play an important role in this new context, since both utilities and electricity consumers frequently trade futures and forward contracts to manage this risk.

Whereas futures contracts are traded on exchanges, forward contracts are traded in over-the-counter (OTC) markets, which has important implications in terms of trading, clearing and settlement procedures and rules. For example, futures contracts do not have credit risk since the clearing house acts as the counterparty for all the futures positions, taking both sides of the trade. In OTC markets, both parties have traditionally assumed considerably high counterparty or default risk. Following the credit crisis, which started in 2007, new regulations affecting the OTC market have arisen and it is more and more frequent that one or both sides demand the counterparty to post some form of collateral to protect against the default risk or to clear OTC trades through a central counterparty (CCP) that operates very much like an exchange clearing house. Besides, traders can easily close out their positions prior to maturity by a reversing trade. In contrast, in the OTC market, replacing a position can certainly be difficult. As closing out positions in forward contracts are not always feasible, forward contracts usually lead to final delivery of the

underlying assets being settled at the end of their life, on maturity. Conversely, futures contracts are daily settled under the marking-to-market process. This daily settlement of futures contracts involves calculating the gains and losses of the futures positions at the end of each trading day, so it can cause severe liquidity problems and may even discourage traders from trading futures contracts in favor of forward contracts, as well as in price transparency. Though both types of contracts are available for negotiation, traders opt for one or the other depending on their preferences.

The majority of forward market trading volumes take place on OTC markets [1]. In Spain, electricity can be traded in the spot market, which was created in January 1998 as a result of the liberalization of the power sector and is managed by the Iberian Market Operator, OMIE; in the Iberian Futures Market, which began trading on 3 July 2006, it can be traded by the Regulated Market Operator, OMIP; in the European Energy Exchange (EEX) by the Futures Markets (from February 2005) and, finally, by the OTC market. In 2016, the futures and OTC trading volume amounted to 196.5 TWh, representing 78.7% of the peninsular electricity demand during that year and a 26% increase over 2005 volumes. Furthermore, in December 2016, OTC trading accounted for 92% of the total futures and forward trading [2]. These figures show the significant preference that Spanish traders exhibit for OTC transactions compared to those carried out in exchanges.

Futures prices and trading volumes are publicly available, contributing to market transparency. However, OTC markets have been traditionally characterized by their lack of transparency in terms of both prices and trading volumes. Given that such information is key for traders, there are private companies that offer real-time trading information as well as historical series of forward contracts prices and volumes they obtain from their network of information providers. Two of the most popular database service providers are Thomson Reuters and Bloomberg, which provide access to market data through Thomson Reuters Eikon and Bloomberg Terminal platforms, respectively.

Thus, among other information, these companies provide series of forward prices distinguishing between various data sources. The disclosed prices are calculated based on price trades, as well as on bid and ask prices collected from their network of informants (usually specialized brokers or financial institutions). Strictly, there are no apparent differences in the methods used to calculate the disclosed forward prices by any of the above-mentioned data providers in expectation that any of the forward price databases anticipates information to the others. Despite this, they offer different price series for the same references. Therefore, it is of interest to know if there are significant differences between the price series provided through the information platforms considered in this study or if, on the contrary, they can be used interchangeably, since it is shown that they offer essentially identical price information, regardless of the data provider.

The reliability of the historical price series is a relevant issue not only to practitioners, but also for many academics who use them to perform their research investigations. The decisions made by the former, as well as the conclusions reached by the latter, are based on the database used.

Furthermore, the rules to calculate the released prices are not made public. Some general guidelines have been received directly from the two data providers, stating the disclosed prices for a particular series and day mainly depend on the trading activity communicated by each of their informants. Particularly, prices normally correspond to the last trade/tick from each informant's internal information. In the case of absence of transactions, the average of (preferably firm) bid and ask prices are used or, ultimately, directly the (preferably firm) bid or ask price.

For that reason, it is of relevance to carry out an econometric analysis to test whether the information provided by each database is essentially the same, or whether significant discrepancies between them can be detected; whether any database systematically anticipates information or, on the contrary, if it merely replicates the information provided by others. In those latter cases, in that the obtained results will be sensitive to the database finally used, choosing one database or another can make a difference.

The access to these platforms to consult and/or to download the available price series is costly. Another contribution of this work is that our results will let practitioners and researchers know in advance whether there are reasons to prefer some databases or price series over others when deciding the type of subscription they are interested in, or, if the amount paid for the subscription is not a problem, when selecting the historical price series that will be used in forecasting and/or hedging models.

So, the main goal of this study was to test statistically significant differences between the Spanish electricity forward prices provided by Thomson Reuters and Bloomberg during the period from January 2010 through September 2016. Additionally, we tested causal relationships between them with the aim of identifying if there are any leading databases that provide information to the others. We also extended the analysis to the German market and repeated the analysis using the series of German electricity forward prices provided by the same provider companies during the period from January 2008 through September 2016.

With a churn rate of 14 in the third quarter of 2016, Germany is the most liquid market in Europe, followed by the UK (churn rate of 4.5) and the Nordic markets (churn rate of 4.1). In Germany, electricity can be traded in the European Power Exchange (EPEX) spot market, in the European Energy Exchange (EEX) futures market or on the OTC market. Just in the third quarter of 2016, the trading volume of both futures and OTC forward was about 1700 TWh. As in the Spanish case, traders in the German derivatives market mostly prefer negotiating OTC contracts to exchange-traded ones. In fact, OTC trading represented approximately 75% of the total futures and forward trading in the fourth quarter of 2016 [3].

Both Thomson Reuters and Bloomberg provide more than one price series referred to the same forward contract and maturity, according to their data source. Therefore, the analysis was carried out in two phases. First, the price series provided by Thomson Reuters and Bloomberg were analyzed separately to detect significant differences between them. Second, as no significant differences within each company's databases were found, one representative series for Thomson Reuters and one representative series for Bloomberg were chosen to compare to between them.

## 2. Literature Review

The comparison of financial databases has been previously addressed in the related literature. On the one hand, a first branch of literature evaluates the presence of errors and/or discrepancies among databases. Thus, [4] compared monthly prices for New York Stock Exchange (NYSE) stocks from 1962 to 1968, available on CRSP/COMPUSTAT merged database and found a few large errors in both databases that, according to the authors, might well affect research results and management decisions based on them. Ref. [5] updated the study of [4] using a price dividend earnings database for Compustat and extended the analyzed period from January 1962 to July 1978 to conclude that the databases increased their accuracy and corrected some of the errors pointed out by [4], so the databases had become more accurate and reliable than before. After those two pioneering studies, research was carried out that focused on financial data by [6] and [7], both centered on bond prices. On the one hand [6] compared exchange quotations from Moody's Bond Record with prices assigned by Merrill Lynch's institutional pricing service and used each set of prices to calculate return and risk measures for industrial bond month-end prices from December 1975 to June 1980. They concluded that bond returns, risk measures and security allocations in portfolio optimization models were highly sensitive to the source of data selected and advised researchers to be careful with the selection of the data source. On the other hand, [7] compared the month-end prices for noncallable government bonds from February 1981 through December 1985 provided by CRSP and Shearson Lehman Brothers. They found that the detected discrepancies between them were due to liquidity reasons and proposed different filters to improve the quality of the data and reduce the discrepancies. Ref. [8] compared rating levels, particularly rating changes for utility and industrial bonds from Moody's, Standard & Poor's and Fitch IBCA, covering the period from January 1991 to March 1995. They concluded that the average rating of

Fitch IBCA was considerably higher than the average rating of Moody's and Standard and Poor (S&P). Ref. [9] examined the series for mutual funds looking for potential errors in the CRSP Mutual Fund by comparing it with the Morningstar Mutual Fund from January 1979 to December 1998. They found discrepancies between them and stated that there existed two bias problems in CRSP database (an omission bias and an upward bias) in any month where there were multiple distributions on the same day. Ref. [10] did a quite thorough comparison of the six major sources for corporate Credit Default Swap prices for the most liquid single name five-year CDS of the components of iTraxx and CDX from 2004 to 2010. They found some specific discrepancies among the databases but concluded that no single database provided quotes that were consistently above or below the quotes from the other databases (For a review on quality problems in financial and business data, we refer to [11]). However, they identified a leader of the credit risk price discovery process among the analyzed databases.

Our aim was to compare forward price series from two well-known data providers (using their own methodologies to calculate them) both in the Spanish and the German electricity markets, as well as to investigate whether any of them could be considered the "first to move" because this anticipates the price changes observed in, or implied from, the others; thereby, to analyze the dynamics of the price discovery process. To do this latter, a vector autocorrelation (VAR) model was employed to study short-run dynamics, whereas long-term relationships were analyzed using a vector correction model (VECM) specification.

### 3. Data

To compare the databases under study in each of the (Spanish and German) markets, we choose the one-month-ahead forward contract price series, due to liquidity reasons. Thus, daily one-month ahead Spanish forward electricity prices (€/MWh) covering the period from 1 January 2010 to 30 September 2016 (Figure 1) and German forward electricity prices (€/MWh) from 1 January 2008 to 30 September 2016 (Figure 2) were used. The study sample was chosen to maximize the number of price series that could be included in the analysis; namely, searching for the sample with data from the highest number of continuous price series.

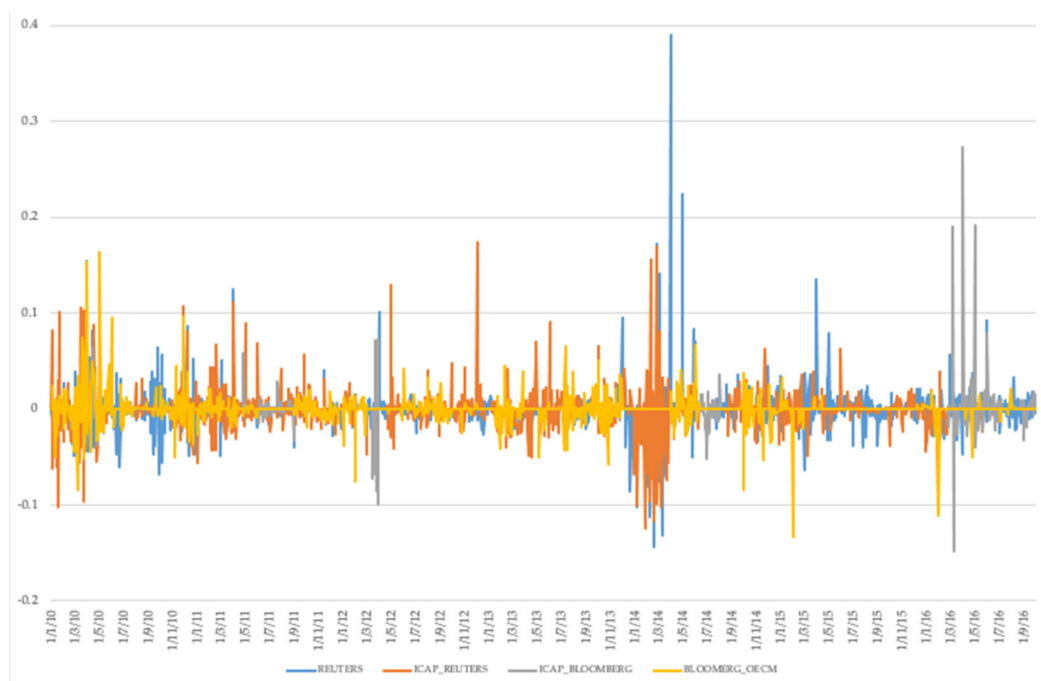


Figure 1. Spanish one-month-ahead forward contract daily return series.



**Figure 2.** German one-month-ahead forward contract daily return series.

The data used were obtained through the download of historical prices at a daily frequency. Within a day, the frequency at which prices are updated is variable since they generally correspond to the last trade in the OTC market communicated by each informant to the data provider. In the absence of transactions, the bid ask average price, or simply one of them (bid or ask) if the other is not available, becomes the disclosed price. Network informants are contacted several times a day to update the disclosed prices. Trades are executed on platforms other than Bloomberg and Thomson Reuters, or through bilateral trading. For the purpose of the present study, we used historical price series containing the last updated price (which would be the equivalent to the closing price in organized exchanges like Futures Markets) for each day.

Table 1 illustrates the differences in data availability. It is clear that all the series did not have the same number of available data. Thus, on the one hand, Spanish OTC contracts had a wide range of availability percentage, from 98.18 to 10.79%. On the other hand, the data availability from the different databases for German OTC contracts was greater than Spain, above 64% in all cases. In general terms, only for the Spanish case, the availability of data was greater in the series provided by Thomson Reuters than in those offered by Bloomberg.

According to Table 1, some of the price series were selected as the most representative ones from each data source for the Spanish and for the German market. Thus, the analysis was finally carried out with two price series from Thomson Reuters and another two from Bloomberg for the Spanish market area (Reuters, Icap Reuters, Icap Bloomberg and Bloomberg OECM), with 45.83% being the minimum percentage of data availability for these series. Consequently, the Bloomberg BBSW and Bloomberg GFI databases were discarded due to the limited availability of data they exhibited during the sample period. Following the same criteria, the analysis for the German market was made using a total of nine price series, five from Thomson Reuters (Reuters, GFI Reuters, TulletPrebon, Icap Reuters and Marex Spectron Reuters) and four from Bloomberg (BBSW Bloomberg, GFI Bloomberg, OECM Bloomberg and Spectron Bloomberg), all with a percentage of data availability above 86%.



**Table 1.** Data availability.

<b>Spain</b>		
	THOMSON REUTERS	%
REUTERS	1729	98.18%
ICAP REUTERS	1431	81.26%
	BLOOMBERG	%
ICAP BLOOMBERG	964	54.74%
BLOOMBERG OECM	807	45.83%
BLOOMBERG BBSW	292	16.58%
BLOOMBERG GFI	190	10.79%
<b>Germany</b>		
	THOMSON REUTERS	%
REUTERS	2271	99.43%
TULLET PREBON REUTERS	2120	92.82%
GFI REUTERS	2098	91.86%
ICAP REUTERS	1998	87.48%
MAREX SPECTRON	1986	86.95%
TRADITION FINANCIAL SERVICES R	1683	73.69%
	BLOOMBERG	%
OECM BLOOMBERG	2231	97.68%
SPECTRON BLOOMBERG	2190	95.88%
GFI BLOOMBERG	2188	95.80%
BBSW BLOOMBERG	2033	89.01%
ICAP BLOOMBERG	1771	77.54%
TRADICIONAL SERVICE B.	1678	73.47%
TULLET PREBON BLOOMBERG	1462	64.01%

In the end, a total of four price series referring to the Spanish electricity one-month-ahead forward contract, two obtained from Thomson Reuters and the other two from Bloomberg (Figure 1), and a total of nine price series referring to the German electricity 1-month-ahead forward contract, were chosen to perform the empirical exercise, due to data availability reasons, which was the first criterion applied to discriminate between the series (Figure 2).

#### 4. Methodology

In order to study the discrepancies between the different price series within and across databases, an analysis based on mean, median and variance equality tests was carried out. Subsequently, to examine the price discovery process of the considered databases, the methodologies of unit root tests, cointegration and vector error correction models (VECM) were applied. Despite the fact that these statistical and econometrical tools are quite standard, an explanation of them is included with the aim of making the study more self-contained.

##### 4.1. Discrepancies Test

To compare pairwise differences between the databases of each of the countries involved in this study, we used the median and variance Tests.

##### 4.1.1. Median Equality Test—Kruskal-Wallis Test

This test is a nonparametric test for determining if samples are originated from the same distribution and does not assume a normal distribution. However, the test does assume an identically shaped and scaled distribution for each series, except for any difference in medians [12].

The H rank test requires that all the observations be ranked together, and the sum of the ranks obtained for each sample. The test statistic is:

$$H = \frac{12}{N(N + 1)} \sum_{g=1}^G \frac{R_g^2}{n_g} - 3(N + 1) \tag{1}$$

where  $n_g$  is the number of observations in group  $g$ ,  $N = \sum n_g$  is the number of observations in all groups,  $R_g$  is the sum of the ranks in group  $g$ ,  $t$  is the number of tied observations in the group and  $T = t^3 - t$ .  $H$  is distributed as  $\chi_{G-1}^2$  under the null hypothesis of equal population medians. The null hypothesis would be rejected when  $H > \chi_{G-1}^2$ .

#### 4.1.2. Variance Equity Test—Levene Test

This test [13] is an inferential statistic used to assess the equality of variances in different samples. It tests the null hypothesis that the population variances are equal. The test statistic,  $W$ , is defined as follows:

$$W = \frac{(N - G) \sum_{i=1}^G n_g (Z_{g.} - Z_{...g})^2}{(G - 1) \sum_{i=1}^G \sum_{j=1}^{n_g} (Z_{g,i} - Z_{g.})^2} \tag{2}$$

where  $G$  is the total number of different groups,  $N$  is the number of observations in all groups,  $n_g$  is the number of observations in group  $g$

$$Z_{g,i} = \left\{ \begin{array}{l} |X_{g,i} - \bar{X}_{g.}|, \\ |X_{g,i} - \hat{X}_{g.}|, \end{array} \right\} \begin{array}{l} \bar{X}_{g.} \text{ is the mean of } g\text{-th group} \\ \hat{X}_{g.} \text{ is the median of } g\text{-th group} \end{array} \tag{3}$$

and  $X_{g,i}$  is the value of the  $i$ -th observation from group  $g$

$$Z_{..} = \frac{1}{N} \sum_{g=1}^G \sum_{i=1}^{N_g} Z_{g,i} Z_{g.} = \frac{1}{N_g} \sum_{i=1}^{N_g} Z_{g,i} \tag{4}$$

$W$  is distributed as an F-distribution with  $G-1$  numerator degrees of freedom and  $N-G$  denominator degrees of freedom, under the null hypothesis of equal variances. The null hypothesis would be rejected if  $W \geq F_{G-1; N-G}$ , since a difference would exist between at least two samples.

### 4.2. Price Discovery Process

To detect information advantages, the stationarity of the series (unit root test), their long-term equilibrium relationships (cointegration) and their short-term and long-term causality (VECM) are analyzed.

#### 4.2.1. Unit Root Test

Financial series typically present nonstationary problems. Ref. [14] noted that if a series has nonstationary problems it can lead us to conclude that a causal relationship exists between two variables when that relationship is really only random.

In order to test whether the series considered in this study were stationary [15] proposed the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test in which the null hypothesis is stationary, whereas the alternative hypothesis is that the series is not stationary.

The KPSS statistic is based on the residuals of the Ordinary Least Squares (OLS) regression of  $y_t$  on the exogenous variables  $x_t$ :

$$y_t = x_t' \delta + u_t \tag{5}$$

The statistical Lagrange Multiplier (*LM*) is defined as:

$$LM = \frac{\sum_t S(t)^2}{T^2 f_0} \quad (6)$$

where  $f_0$  is an estimator of the residual spectrum at frequency zero,  $S(t)$  is a cumulative residual function:  $S(t) = \sum_{\tau=1}^t u$  based on the residuals  $u_t = y_t - x_t' \hat{\delta}$ , and  $T$  is the total number of observations. The null hypothesis to be tested is the stationarity of the series.

#### 4.2.2. Cointegration Analysis

Economic theory suggests the existence of equilibrium relationships in the long-term between databases providing similar or related information, although they can fluctuate individually out of equilibrium for some time due to discrepancies in the information regularly provided by the informants. Ref. [16] proposed a procedure, based on the principle of likelihood ratio under the assumption of normality, to test for cointegration. This procedure uses the vector error correction model (VECM) that does not distinguish, a priori, any order of causality between variables.

The starting point is the methodology of vector autoregressive (VAR) from the following expression:

$$x_t = A_1 * x_{t-1} + \varepsilon_t \quad (7)$$

where  $x_t$  and  $\varepsilon_t$  are vectors  $n \times 1$  and  $A_1$  is the parameters matrix ( $n \times n$ ). Subtracting  $x_{t-1}$  in both parts of the equation we obtain:

$$\Delta x_t = A_1 x_{t-1} - x_{t-1} + \varepsilon_t = (A_1 - I) * x_{t-1} + \varepsilon_t = \pi * x_{t-1} + \varepsilon_t \quad (8)$$

where  $I$  is the identity matrix ( $n \times n$ ) and  $\pi$  is  $(A_1 - I)$ . The range of  $\pi$  indicates the number of independent cointegration vectors, which can be obtained by checking the significance of the characteristic root (eigenvalues) of  $\pi$  ( $\lambda_I$ ) that establishes the matrix rank. There are several ways to generalize the model: for example, the inclusion of a drift in the equation, the inclusion of a constant in the cointegrating vector, or both at once.

If the time series that make up  $x_t$  are not cointegrated, the range of  $\pi$  is zero and all its characteristic roots are equal to 1. The Johansen cointegration test for determining the number of characteristic roots that are different from the unit can be determined using the two following statistics.

The trace statistic tests the null hypothesis that the number of cointegrating vectors is less than or equal to  $r$ , against the alternative hypothesis that this is not the case:

$$\lambda_{trace}(r) = -T * \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i) \quad (9)$$

where  $\hat{\lambda}_i$  are the estimate values of the characteristic roots obtained by estimating  $\pi$ , and  $T$  is the total number of observations.

The critical values were obtained by [17], although [18] recalculated these values through the Monte Carlo process.

#### Short and Long-Term Causality Relationships

The vector error correction model (VECM) is a vector autocorrelation model (VAR) that is designed to be used with nonstationary series that we know are cointegrated. The VECM restricts the long-term behavior of the endogenous variables to converge to the cointegration relationship, while allowing short-term dynamic adjustment. Moreover, Granger (1983) showed that if the series were cointegrated, the VECM model improved the VAR model in efficiency and forecasting.



Thus, the VECM representation illustrates the relationship between the concepts of cointegration and the Granger causality, with the causality between the series analyzed through the elements of the VECM.

$$\begin{aligned}\Delta Y_t &= \alpha_1 + \sum_{i=1}^p \gamma_i \Delta Y_{t-1} + \sum_{j=1}^q \delta_j \Delta X_{t-j} + \beta_1 u_{t-1} + \epsilon_{t1} \\ \Delta X_t &= \alpha_2 + \sum_{i=1}^r \gamma'_i \Delta Y_{t-1} + \sum_{j=1}^s \delta'_j \Delta X_{t-j} + \beta_2 u_{t-1} + \epsilon_{t2}\end{aligned}\quad (10)$$

where  $\beta_1$  and  $\beta_2$  coefficients measure the speed of endogenous variable adjustment towards equilibrium, and  $\mu_{t-1}$  is the residual of cointegration regression delayed one period. If the error correction term is significant in both equations ( $\beta_1 \neq 0$  and  $\beta_2 \neq 0$ ), there exists bidirectional long-term causality (long run causality depends upon significance of long run relationship and is tested through lagged error correction term which is derived from long run equilibrium relationship). so that none of the variables can be considered weakly exogenous with respect to the parameters of the other equation. However, according to [19] the condition that there is no Granger causality is necessary but not sufficient for weak exogeneity. If the null hypothesis is accepted ( $\delta_j = 0$  for  $j = 1, \dots, q$ ) then we can say that  $X$  does not cause (help to predict)  $Y$  in the short-term. Short run Granger causality is based on the joint significance of first difference variable in the vector error correction equation. If it is accepted that  $\gamma'_i = 0$  for  $i = 1, \dots, r$  then we can say that  $Y$  does not cause  $X$  in the short-term. The joint hypothesis testing was done through the Wald test using F statistics and/or  $\chi^2$ , and the numbers of lags were determined using the Akaike information criterion.

## 5. Empirical Results

The empirical analysis was organized as follows. First, a main descriptive analysis was made of the characteristics of the series. Second, the mean, median and variance equality tests were performed to find out whether there were statistical divergences between the analyzed databases. Lastly, the analysis to determine lead-lag relationships of the studied databases was carried out through the vector error correction model (VECM).

### 5.1. Main Descriptive Statistics

Table 2 shows the main descriptive statistics for electricity one-month-ahead forward contract prices of each price series included in the present study, differentiating between the Spanish and the German market. At first sight, all the price series within each database appear to be very close in terms of mean, median and variance. However, this preliminary result must be statistically tested.

For the Spanish case, according to the results displayed in Table 2 (Panel A), the mean values of all the series were quite close to each other, except for the OECM Bloomberg which was around 4 Euros/MWh lower. The median values and the minimum values of the four series were virtually the same. However, some discrepancies were observed on the maximum values between the series provided by Bloomberg (around 59 Euros/MWh) and by Reuters (around 64 Euros/MWh), which translated into a higher range for the latter (40 versus 34). The skewness coefficients were negative, indicating heavier left tails when compared to those of the normal distribution, and the kurtosis coefficients were slightly higher than that corresponding to the standard normal. The absence of normality of the price series was confirmed by the Jarque-Bera statistics, for which in all cases the null hypothesis of normality was rejected.

Table 2. Descriptive statistics.

Spanish Market	OECM BLOOMBERG	ICAP BLOOMBERG	ICAP REUTERS	REUTERS	
Mean	42.73	46.61	46.93	46.91	
Median	48.20	48.25	48.25	48.20	
Maximum	59.40	59.40	63.75	63.75	
Minimum	25.45	25.45	24.00	24.00	
Standard Deviation	7.11	7.31	7.27	7.21	
Skewness	−0.92	−0.85	−0.94	−0.93	
Kurtosis	3.47	3.17	3.57	3.57	
Jarque-Bera	121.15	116.04	231.91	271.79	
<i>p</i> -value	0.00	0.00	0.00	0.00	
Observations	807	964	1431	1729	
German Market	BBSW BLOOMBERG	GFI BLOOMBERG	OECM BLOOMBERG	SPECTRON BLOOMBERG	
Mean	44.65	42.97	43.00	43.038	
Median	41.4	39.9	40.00	39.90	
Maximum	98.23	98.25	98.50	98.45	
Minimum	27.65	21.05	21.10	21.10	
Standard Deviation	13.17	13.67	13.62	13.74	
Skewness	1.26	1.16	1.15	1.14	
Kurtosis	4.75	4.56	4.60	4.48	
Jarque-Bera	794.69	709.07	733.78	673.53	
<i>p</i> -value	0.00	0.0	0.00	0.00	
Observations	2033	2187	2231	2190	
German Market	GFI REUTERS	ICAP REUTERS	MAREX SPECTRON REUTERS	REUTERS	TULLET PREBON REUTERS
Mean	42.06	41.33	41.76	43.03	40.89
Median	39.43	38.55	39.00	40.10	38.70
Maximum	98.25	99.25	92.00	98.45	91.75
Minimum	21.05	21.05	21.10	21.10	20.95
Standard Deviation	12.76	12.26	12.21	13.65	11.11
Skewness	1.22	1.40	0.83	1.15	0.75
Kurtosis	5.29	6.37	3.49	4.56	3.52
Jarque-Bera	984.83	1593.26	246.20	731.32	222.90
<i>p</i> -value	0.00	0.00	0.00	0.00	0.00
Observations	2098	1997	1986	2271	2120

The results obtained for the German market shown in Table 2 (Panel B) also indicated quite similar mean, median, maximum and minimum values, with the only exceptions being lower minimum values from the series Marex Spectron and Tullet Prebon provided by Reuters. The skewness and kurtosis coefficients, together with the Jarque-Bera statistic, led us to reject the hypothesis that the series were normally distributed. Broadly speaking, the series provided by Reuters sources seemed to exhibit lower volatility than those provided by Bloomberg.

Lastly, when comparing both markets, higher mean values of Spanish prices compared to German prices were observed. Additionally, the Spanish (German) OTC one-month-ahead forward prices were negatively (positively) skewed, which indicates a greater (lower) probability of obtaining a value below the mean than above it. Finally, according to the standard deviation values, German prices exhibited higher variability than Spanish prices, in general terms.

### 5.2. Equality Analysis

Two price series for the same asset reported by different information sources should theoretically be very close to each other. However, there may also be differences between them that could change properties of the data. For that reason, it is important to test whether these differences are statistically significant. To do so, we used the tests of [12,13], whose results for the Spanish and the German markets are shown in Tables 3 and 4, respectively. It can be observed that there were no significant discrepancies, since in all cases the *p*-value was greater than the significance level of 5%.

**Table 3.** Test for differences (Spanish market).

Levene Test	REUTERS	BLOOMBERG OECM
ICAP REUTERS	0.0040 (0.9494)	
ICAP BLOOMBERG		0.0008 (0.9774)
Kruskal Wallis Test	REUTERS	BLOOMBERG OECM
ICAP REUTERS	0.0029 (0.9570)	
ICAP BLOOMBERG		0.001921 (0.9650)

(\*) Significant at 5%.

**Table 4.** Test for differences (German market).

Levene Test	BBSW BLOOMBERG	GFI BLOOMBERG	OECM BLOOMBERG	
BBSW BLOOMBERG				
GFI BLOOMBERG	0.0000 (0.9963)			
OECM BLOOMBERG	0.0016 (0.9681)	0.0085 (0.9264)		
SPECTRON BLOOMBERG	0.0048 (0.9446)	0.0139 (0.9061)	0.0005 (0.9815)	
	FI REUTERS	ICAP REUTERS	MAREX SPECTRON REUTERS	REUTERS
GFI.R				
ICAP.R	0.0431 (0.8354)			
MAREXSPECTRON.R	0.7636 (0.3822)	0.0162 (0.8986)		
REUTERS	0.1242 (0.7245)	0.1222 (0.7267)	0.1848 (0.6673)	
TULLET PREBON.R	0.4679 (0.4940)	0.1331 (0.7153)	0.1438 (0.7045)	0.0020 (0.9643)
Kruskal Wallis Test	BBSW BLOOMBERG	GFI BLOOMBERG	OECM BLOOMBERG	
BBSW BLOOMBERG				
GFI BLOOMBERG	0.0001 (0.9908)			
OECM BLOOMBERG	0.0004 (0.9836)	0.0000 (0.9976)		
SPECTRON BLOOMBERG	0.0001 (0.9902)	0.0004 (0.9828)	0.0007 (0.9787)	
	GFI REUTERS	ICAP REUTERS	MAREX SPECTRON R	REUTERS
GFI REUTERS				
ICAP REUTERS	0.1089 (0.7414)			
MAREX SPECTRON.R	0.0094 (0.9229)	0.0492 (0.8245)		
REUTERS	0.0211 (0.8845)	0.0001 (0.9903)	0.0800 (0.7773)	
TULLET PREBON.R	0.8218 (0.3647)	0.6076 (0.4357)	0.9337 (0.3339)	0.5895 (0.4426)

(\*) Significant at 5%.

### 5.3. Stationarity

Table 5 displays the KPSS [15] unitary root test results. As can be observed, it was verified that the time series of Spanish and German forward prices were not stationary, whereas they were so when transformed into first differences. Therefore, all the price series exhibited a unit root.

Table 5. KPSS Test.

Spanish OTC Market		
Data Provider	Levels	1st Difference
Reuters	0.3599 *	0.0609
ICAP Reuters	0.4457 *	0.5788
Bloomberg OECM	0.7889 *	0.0609
ICAP Bloomberg	0.7241 *	0.1483
German OTC Market		
Data Provider	Levels	1st Difference
BBSW.B	0.2099 *	0.0405
GFI.B	0.1863 *	0.0343
OECM.B	0.19059 *	0.0363
SPECTRON.B	0.1818 *	0.0631
GFI.R	0.1944 *	0.03334
ICAP.R	0.2517 *	0.0715
REUTERS	0.1735 *	0.0380
TULLET PREBON.R	0.3498 *	0.0251
MAREX SPECTRON.R	0.2592 *	0.0257

(\*) Significant at 5%.

#### 5.4. Price Discovery Process

As previously mentioned, OTC prices are not publicly available. This is the reason why information provider companies, such as Thomson Reuters and Bloomberg, offer (historical and online) OTC price information to potential traders in the market and other companies in the sector that might well be interested in obtaining forward price references. Thomson Reuters and Bloomberg collect price information through daily surveys made to market participants who act as informants for them. As previously mentioned, sometimes they are informed about transaction prices, but others are merely bid or ask prices. To calculate prices, a criteria priority order is generally followed: the average price of transactions; in absence of transactions, the bid and ask average (preferably firm) prices; the bid or ask average (preferably firm) prices; the bid or ask (preferably firm) prices.

Given the lack of transparency of the OTC market, it might be the case that some price series (or database) systematically advanced information to the remaining price series, thereby contributing to the price discovery process. Therefore, it would be interesting to ascertain whether there are databases that lead the price discovery process, which are then followed by other databases. With that objective in mind, the Vector Error Correction Model (VECM) [16] and the Granger's causality test [20] were used.

We apply the logarithm of the price to smooth the series and compare returns in the VECM. Then, we analyzed if the series were cointegrated using the Johansen's test. In Table 6, all the permutations between two available databases are done, and the results indicate that at least one cointegration vector existed between them.

Therefore, we can analyze the price discovery process using a VECM.

Regarding the series prices provided by Thomson Reuters (Icap Reuters and Reuters), the obtained results (displayed in Table 7) showed, on the one hand, the absence of short-term causality between them ( $p$ -value is higher than 5%) and, on the other hand, a two-way long-term causal relationship.

Table 6. Cointegration test.

Spanish OTC Market				
TRACE TEST				
$r = 0$				
REUTERS ICAP BLOOMERG	ICAP REUTERS 187.7351 (0.0001) *	BLOOMBERG OECM 44.0436 (0.0000) *		
$r \leq 1$				
REUTERS ICAP BLOOMERG	ICAP REUTERS 1.0289 (0.3105)	BLOOMBERG OECM 7.9063 (0.0049)		
German OTC Market				
TRACE TEST				
$r = 0$				
ICAP REUTERS MAREX SPECTRON R REUTERS TULLET PREBON REUTERS	GFI REUTERS 131.2220 (0.0001) * 130.4228 (0.0001) * 110.3885 (0.0001) * 148.1309 (0.0001) *	ICAP REUTERS 154.1821 (0.0001) * 93.80135 (0.0000) * 154.3541 (0.0001) *	MAREX SPECTRON R 27.53388 (0.0005) * 194.6511 (0.0001) *	REUTERS 120.6594 (0.0001) *
$r \leq 1$				
ICAP REUTERS MAREX SPECTRON R REUTERS TULLET PREBON REUTERS	GFI REUTERS 8.5778 (0.0034) * 3.7770 (0.0520) 7.6936 (0.0055) 10.5588 (0.0012) *	ICAP REUTERS 1.2956 (0.2550) 12.8854 (0.0003) * 5.9949 (0.0143)	MAREX SPECTRON R 0.0132 (0.9083) 0.4503 (0.5022)	REUTERS 0.7122 (0.3987)

(\*) Significant at 5%.

Table 7. Reuters-Short- (ST) and long-term (LT) causality for Spanish case.

Data Provider	REUTERS ICAP		REUTERS	
	ST	LT	ST	LT
REUTERS ICAP REUTERS	0.5179 (0.4718)	17.03691 (0.0000) *	1.6593 (0.1977)	54.29501 (0.0000) *

(p value), (\*) Significant coefficient at 5%. The independent variables are by rows, and the dependent variables by columns.

Given that no significant differences between the series provided by Thomson Reuters were found, we chose one as a representative database of this group. The chosen series was the one called Reuters because, in the absence of unidirectional causal relationships that justify the choice of one with respect to the other, the percentage of available data (98.18%) was greater than that for Icap Reuters (81.26%).

With regard to the series provided by Bloomberg (Bloomberg OECM and ICAP Bloomberg), the obtained results are shown in Table 8. We observed the existence of bidirectional causality in the short term between both sources, while in the long term, it was Icap Bloomberg that caused Bloomberg OECM. Therefore, in this case, the database chosen as representative of the Bloomberg database group, and that we used to continue the comparative analysis between Reuters and Bloomberg for the Spanish market, was Icap Bloomberg.

**Table 8.** Bloomberg-Short- (ST) and Long-term (LT) causality for Spanish case.

Data Provider	BLOOMBERG OECM		ICAP BLOOMBERG	
	ST	LT	ST	LT
BLOOMBERG OECM	3.9783 (0.0461) *	6.000934 [0.0143] *	3.8834 (0.0488) *	2.2387 (0.1346)
ICAP BLOOMBERG				

(p value), (\*) Significant coefficient at 5%. The independent variables are by rows, and the dependent variables by columns.

Table 9 shows the short-term causality results obtained for the Thomson Reuters databases. Based on the obtained results, the databases with the highest number of causality relationships in the short term were Marex Spectron Reuters and Reuters, since both caused all the remaining databases. Bidirectional causality relationships were found between: GFI Reuters and Tullet Prebon Reuters; Icap Reuters and Reuters; Icap Reuters and Tullet Prebon Reuters; Marex Spectron Reuters and Reuters and, finally, between Reuters and Tullet Prebon Reuters. GFI Reuters caused both Tullet Prebon Reuters and Icap Reuters. Regarding the long-term, GFI Reuters and Reuters caused all other databases (Table 10). Therefore, based on the obtained results, the database selected as representative of the group was Reuters, since it was the database that caused all others in both the short and long term.

**Table 9.** Reuters short-term causality for the German case.

Data Provider	GFI REUTERS	ICAP REUTERS	MAREX SPECTRON	REUTERS	TULLET PREBON R
GFI		48.7092	5.9352	2.4801	45.1768
REUTERS		(0.0000) *	(0.0514)	(0.2894)	(0.0000) *
ICAP	2.5667		1.007052	3.8855	13.0613
REUTERS	(0.1091)		(0.3156)	(0.0487) *	(0.0045) *
MAREX	144.7857	38.7753		13.0516	8.4067
SPECTRON	(0.0000) *	(0.0000) *		(0.0045) *	(0.0383) *
REUTERS	172.2457	97.5269	10.8444		120.8701
	(0.0000) *	(0.0000) *	(0.0126) *		(0.0000) *
TULLET	38.3878	28.2449	6.1990	15.4171	
PREBON R	(0.0000) *	(0.0000) *	(0.1023)	(0.0172) *	

(p value), (\*) Significant coefficient at 5%. The independent variables are by rows, and the dependent variables by columns.

**Table 10.** Reuters long-term causality for the German case.

Data Provider	GFI REUTERS	ICAP REUTERS	MAREX SPECTRON	REUTERS	TULLET PREBON R
GFI		33.0616	5.2809	5.5492	50.1703
REUTERS		(0.0000) *	(0.0216) *	(0.0185) *	(0.0000) *
ICAP	29.4196		0.22067	1.3605	48.0401
REUTERS	(0.0000) *		(0.6385)	(0.2434)	(0.0000) *
MAREX	55.2861	97.0180		0.0067	61.4775
SPECTRON	(0.0000) *	(0.0000) *		(0.9348)	(0.0000) *
REUTERS	44.9617	79.1424	4.1395		38.5629
	(0.0000) *	(0.0000) *	(0.0419) *		(0.0000) *
TULLET	8.1534	37.8782	1.6994	0.2184	
PREBON R	(0.0043) *	(0.0000) *	(0.1924)	(0.6402)	

(p value), (\*) Significant coefficient at 5%. The independent variables are by rows, and the dependent variables by columns.

Regarding Bloomberg’s data sources, GFI Bloomberg and Spectron Bloomberg were the databases that exhibited the greatest number of causal relationships in the short-term. Table 11 shows the results obtained. Thus, GFI Bloomberg and Spectron Bloomberg affected two databases, while the others causes only one. GFI Bloomberg affected BBSW



Bloomberg and Spectron Bloomberg. Spectron Bloomberg causes GFI Bloomberg and OECM Bloomberg.

**Table 11.** Bloomberg short-term causality for the German case.

Data Provider	BBSW BLOOMBERG	GFI BLOOMBERG	OECM BLOOMBERG	SPECTRON B
BBSW BLOOMBERG		4.7678 (0.0290) *	1.1954 (0.2742)	2.8168 (0.0933)
GFI BLOOMBERG	9.3981 (0.0022) *		3.0716 (0.0797)	18.3819 (0.0000) *
OECM BLOOMBERG	2.6412 (0.1041)	1.2173 (0.2699)		13.3142 (0.0003) *
SPECTRON BLOOMBERG	0.0518 (0.8199)	8.6895 (0.0032) *	8.5891 (0.0034) *	

(*p value*), (\*) Significant coefficient at 5%. The independent variables are by rows, and the dependent variables by columns.

According to the results obtained, and as indicated in Table 12, Spectron Bloomberg, OECM Bloomberg and BBSW Bloomberg caused, in the long term, all the others. On the other hand, GFI Bloomberg did not exhibit any causal relationship in the long term.

**Table 12.** Bloomberg long-term causality for the German case.

Data Provider	BBSW BLOOMBERG	GFI BLOOMBERG	OECM BLOOMBERG	SPECTRON B
BBSW BLOOMBERG			26.6547 (0.0000) *	18.3600 (0.0000) *
GFI BLOOMBERG	0.6434 (0.4225)	67.0606 (0.0000) *	0.5903 (0.4423)	0.0367 (0.5404)
OECM BLOOMBERG	12.5289 (0.0004) *	64.1931 (0.0000) *		9.9729 (0.0016) *
SPECTRON B	29.4051 (0.0000) *	91.0611 (0.0000) *	41.9113 (0.0000) *	

(*p value*), (\*) significant coefficient at 5%. By independent variable rows, by dependent variable columns.

In this case, because Spectron Bloomberg is the one that causes all the others in the long term, and in the short term it was one of the two databases that causes a greater number of databases, specifically two. We chose this data source, among those provided by Bloomberg, to perform the final analysis together with Reuters.

The next step was to test whether there were significant differences between Reuters and Bloomberg through the comparison of the representative series from each database provider and each country. First, the Kruskal-Wallis and Levene tests were carried out to examine whether there were discrepancies in terms of median and variance. As shown in Tables 5 and 6, the series were nonstationary and cointegrated, so next we proceeded to contrast the existence of causal relationships between them.

Tables 13 and 14 show the results obtained from the Levene and Kruskal-Wallis tests and from the cointegration test, respectively. As can be seen in Table 13, there was no evidence of significant differences in terms of variance and median. In addition, Icap Bloomberg and Reuters were also shown to be cointegrated (Table 14).

**Table 13.** Levene and Kruskal Wallis Test.

Levene	Kruskal Wallis
0.0364 (0.8487)	0.5636 (0.4528)

**Table 14.** Cointegration test.

<b>Trace</b>	
$r = 0$	$r \leq 1$
102.4083 (0.0001)	10.0917 (0.0015)

Finally, to test the short and the long-term causality between them, the VECM and the Wald test were used. The obtained results, shown in Table 15, led us to conclude that, in the long-term, it was Reuters that influenced Icap Bloomberg, whereas there were no causal relationships between them in the short-term.

**Table 15.** Short- (ST) and long-term (LT) causality.

<b>Data Provider</b>	<b>ST</b>	<b>LT</b>
REUTERS	0.0015 (0.9692)	2.2806 (0.1310)
ICAP BLOOMBERG	2.4416 (0.1182)	24.4857 (0.0000) *

\*Accept causality at 1% level.

In this section, an analogous analysis is made to the previous section with the databases Reuters and Spectron Bloomberg for the case of Germany.

Repeating the analysis for the previously selected forward price series from Reuters and Bloomberg for the German market (Reuters and Spectron Bloomberg), it can be concluded that there were no significant differences between them in terms of median and variance (Table 16) and that they were cointegrated, according to the Johansen test results (Table 17). Furthermore, as displayed in Table 18, the obtained results indicate the presence of a causality relationship from Reuters to Spectron Bloomberg in the long-term, whereas the causality relationship between them in the short-term was bidirectional.

**Table 16.** Levene Test and Kruskal Wallis Test.

<b>Levene</b>	<b>Kruskal Wallis</b>
0.0599 (0.8067)	0.011407 (0.9149)

**Table 17.** Cointegration test.

<b>Traza</b>	
$r = 0$	$r \leq 1$
64.6090 (0.0000)	4.9928 (0.0254)

**Table 18.** Short- (ST) and long-term (LT) causality.

	<b>ST</b>	<b>LT</b>
<b>SPECTRON BLOOMBERG</b>	31.9607 (0.0000) *	6.0042 (0.0143) *
<b>REUTERS</b>	15.2025 (0.0017) *	1.4849 (0.2230)

\*Accept causality at 1% level.

## 6. Conclusions

In contrast to futures exchanges, OTC markets have traditionally suffered from a lack of price transparency. Knowing the price at which trades are made is key for market participants, so that they can have a price reference for pricing decisions. In addition, price forecasts are based on valuation models that are estimated using historical data. Therefore, it is crucial for both practitioners and researchers to have sufficiently reliable historical price databases. The motivation of this study was to determine whether the historical data related to the Spanish and German OTC forward electricity markets (particularly, we

focused on the one-month-ahead contract) provided by the two main financial information providing companies, Thomson Reuters and Bloomberg, essentially contained the same information or whether there were significant differences between them. In this latter case, we also tested if there were leaders and followers among these databases.

It is of note that each company offers price series of the same forward contract from several sources, both for Spanish and German market. One first result was that the availability of data for the Spanish market was generally higher in the series offered by Thomson Reuters than those by Bloomberg during the studied period. This was not so clear for the German market, where both companies provided very high data availability together with a greater number of sources (six referring to the German market versus two referring to the Spanish market provided by Reuters and seven referring to the German market versus four for the Spanish market provided by Bloomberg).

Secondly, we found that there were not significant differences among the price series related to the OTC one-month-ahead contract provided by Thomson Reuters from different sources, both for Spanish and German markets. The same held for the price series provided from different sources by Bloomberg. This result is relevant for the users of these databases because it implies that they would only need to use and/or subscribe to one of the databases provided by these companies, preferably the one that has been highlighted in this work as representative, based on the number of causality relationships and the availability of data; i.e. the series Reuters (among those of Thomson Reuters) and the series Icap Bloomberg (among those of Bloomberg) for the Spanish case, and the series Reuters and Spectron Bloomberg (among those of Thomson Reuters and Bloomberg, respectively) for the German case.

Thirdly, both for Spanish and German markets, after comparing what are referred to in this work as “representative” price series of Thomson Reuters and Bloomberg, it was obtained that they are reliable enough, since they presented similar price information, which implies that the use of both databases should lead to comparable results.

Lastly, a unidirectional causality relationship was detected in the long-term from the price series called Reuters (representative of Thomson Reuters) towards the price series called Icap Bloomberg (representative of Bloomberg) for the Spanish market in the long-term, indicating that the Reuters database could help better predict the behavior of the Bloomberg database. Nevertheless, no causality relationships were uncovered in the short-term. Therefore, these results do not allow us to conclude that a data provider systematically advances information to the other.

Similarly, in the German market, a causal relationship was shown in the long-term from the representative price series of Thomson Reuters, also called Reuters, towards the representative series of Bloomberg, called Spectron Bloomberg, showing that the Reuters database was able to better predict the behavior of the one by Bloomberg. Additionally, opposite to what was obtained for the Spanish market, there was evidence for a bidirectional causal relationship in the short-term. Thus, results on whether one database systematically advances information to the other are not conclusive.

**Author Contributions:** Conceptualization, F.C. and D.F.; methodology, F.C., D.F. and Á.C.; software, Á.C. and F.C.; validation, F.C., D.F. and Á.C.; formal analysis, F.C. and D.F.; investigation, F.C., D.F. and Á.C.; resources, Á.C.; data curation, Á.C.; writing—original draft preparation F.C., D.F. and Á.C.; writing—review and editing, F.C. and D.F.; visualization, F.C. and D.F.; supervision, F.C. and D.F.; project administration, F.C. and D.F.; funding acquisition, F.C. and D.F. All authors have read and agreed to the published version of the manuscript.

**Funding:** Financial support from the Spanish Ministry of Science and Innovation and FEDER (Project PGC2018-093645-B-100) is gratefully acknowledged.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Data are available upon subscription to Thomson Reuters and Bloomberg.

**Acknowledgments:** This work was supported by the Spanish Ministry of Science and Innovation and FEDER (Project PGC2018-093645-B-100).

**Conflicts of Interest:** The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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