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Predicting Post-Production Biomass Prices

Aleksandra Górna [1,*], Alicja Szabelska-Beręsewicz [2], Marek Wieruszewski [3], Monika Starosta-Grala [1], Zygmunt Stanula [1], Anna Kożuch [4,*] and Krzysztof Adamowicz [1]

1 Department of Forestry Economics and Technology, Faculty of Forestry and Wood Technology, Poznan University of Life Sciences, Wojska Polskiego 28, 60-637 Poznan, Poland; krzysztof.adamowicz@up.poznan.pl (K.A.)
2 Department of Mathematical and Statistical Methods, Poznan University of Life Sciences, Wojska Polskiego 28, 60-637 Poznan, Poland
3 Department Mechanical Wood Technology, Faculty of Forestry and Wood Technology, Poznan University of Life Sciences, Wojska Polskiego 28, 60-637 Poznan, Poland
4 Department of Forest Resources Management, Faculty of Forestry, University of Agriculture in Krakow, Al. 29-Listopada 46, 31-425 Krakow, Poland
* Correspondence: aleksandra.gorna@up.poznan.pl (A.G.); a.janusz@ur.krakow.pl (A.K.)

Abstract: This paper presents the application of prediction in the analysis of market price volatility in Polish conditions of wood processing by-products in the form of biomass. The ARIMA model, which takes into account cyclical, seasonal, irregular fluctuations of historical data on the basis of which the forecast and long-term trends of selected wood products were made, was used in predicting prices. Comparisons were made between the ARIMA prediction method and the multiplicative Winters–Holt model. During the period studied (2017–2022), the changes in the market price of biomass were characterized by a wide spread of values. On average, the price of these products increased from 2017 to the end of 2022 by 125%. The price prediction analysis showed seasonal fluctuations in the case of wood chips. The uncertainty in price prediction is due to changes in supply resulting from the influence of global factors. The Diebold–Mariano test of matching accuracy confirms that the price prediction of the analyzed by-product sorts using the ARIMA and WH models is possible. The conclusion reached by comparing these two methods is that each can be used under certain market conditions of certain assortments. In the case of a stable wood product, the choice of the ARIMA model should be resolved, while in the case of price volatile products, WH will be a better choice. The difference between the predicted and actual price with ARIMA ranged from 2.4% to 11.6% and for WH from 3.7% to 29.8%.

Keywords: timber market; wood biomass prices; prediction; seasonality of supply; cyclicality; woodchips; sawdust; bark; ARIMA; Winters-Holt

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1. Introduction

The management process of woody biomass resources seeks to increase the importance of reducing negative environmental impacts. This is influenced by the increasing importance of managing by-products in production processes, or the so-called waste [1–3]. The growing awareness of the negative consequences of the use of fossil raw materials use, which leads to the favorable view of renewable raw materials [4], increases the proportion of decisions and actions taken by producers and consumers who take into account environmental decision-making directions and ecological policies of biomass management. The result is an effort to maximize the use of raw materials and waste materials in the production process as well as the transition to "zero waste" [5–8]. Increased use of renewable raw materials tends to be the direction of wood-processing-related companies [9]. The timber industry is an example of an industry where the total utilization of wood raw material is possible. Due to the nature of processing, by-products are generated that are consumed in the original enterprise or processed in other branches of the industry. In practice, this means the production of timber products existing alongside the potential for reuse and recycling in the generation of so-called waste or by-products [10]. Such opportunities and activities translate directly into economic and environmental benefits, influencing the formation of a neutral environment for the circulation of wood biomass [11]. Processing hard-to-reach post-disaster wood into biomass can be a good solution for preventing energy biomass shortages [12].

The largest processing potential in the timber industry is in the lumber industry. Wood processing generates both finished and by-products. By-products, due to their low processing and lack of chemical contamination, can be used for energy purposes. The goal of sawmill enterprises is to improve profitability with the stable use of raw material resources. It is important to be able to quickly adjust the product price to economic needs and market changes. The activities of wood-processing plants are based on making price evaluations adapted to demand, including in the area of supply of energy biomass. These activities are limited to providing access to by-products such as woodchips, sawdust and bark. The industry's management affects social goals, which is confirmed by the economic as well as environmental and social aspects [13].

Volatile economic conditions are increasing the pressure on financial management and the need to show high financial performance. According to positive accounting theory, increasing risk is associated with the phenomenon of earnings management manipulation. Central European companies manipulate earnings to a similar extent, with Slovak, Czech and Hungarian companies increasing accounting profit to a greater extent than Polish companies [14–16].

Under Polish market conditions, if the sawdust and woodchips in question meet the requirements of regulations, they can be qualified as a by-product. The concept of "by-product" was introduced in Article 5 of Directive 2008/98/EC of the European Parliament and of the Council No. 2008/98/EC on waste and repealing certain directives [17], hereinafter referred to as "Directive 2008/98/EC". The Polish legal provision of Article 10 of the Waste Act [18] has an analogous wording. In these definitions, a material or substance is given the status of a by-product if it is a material resulting from a production process, the primary purpose of which is not to produce it, but to further use the substance or such subjects, and these can be used directly without any further processing. It should be emphasized that a by-product is not waste, and therefore is not subject to the requirements of broadly defined "waste law". Sawdust and woodchips, which are generated as a residue of the production process, can be used both in production processes and in other processes (e.g., processed into wood products, directly burned, or processed into other solid and liquid fuels). This type of biomass, as well as its physical and chemical parameters, are included in the framework quality requirements of a given energy group or else are directly restricted in how the biomass can be used. The quality requirements for solid biomass have a common reference source, which is the European standard PN-EN 14961-1 [19,20].

Sawdust and shavings are generated by sawing and cutting wood. Their shape depends on the tools used. In practice, they are considered to be bulk materials that are a by-product of sawing roundwood in a wet state (moisture content above 30%) and processing sawn materials. The structure of shavings is practically the same as that of the processed material while, as a by-product, it has a varied shape structure [21].

An additional product of wood processing is bark, which consists of all tissues outside the vascular cambium cells. Wood bark is much thinner than the trunk's woody part. Under the conditions of roundwood processing, the bark is removed from the side of the trunk to reduce tool wear. The resulting product is used as an energy material and as a product in horticulture or panel material production [22].

The introduction of increased use of by-products contributes to reducing the consumption of wood as well as fossil fuels. Actions carried out by companies allow for the successive increase in the value of these products in the energy balance, as defined by the 2021–2030 goals of increasing the share of renewable energy in total energy consumption and increasing energy efficiency by at least 32% [23]. Therefore, it is advisable to address this subject, especially given the narrow number of data from the literature and scientific studies on economic factors shaping the potential use of industrial woody biomass. Most of the studies are related to the use of forest biomass and verification of the prediction of price changes in forest biomass [24,25]. In order to effectively assess the sustainability of biomass utilization, it is necessary to carry out an analysis of raw material abundance and economic calculation of post-production biomass.

Given the urgent need to switch to low-carbon energy carriers, waste wood resources could provide an alternative energy resource and reduce emissions at the same time. Various species of waste wood find applications in energy processing using modern processing techniques. Energy from low-polluting processed wood waste will provide advantages over fossil fuels [26–28].

To analyze the economic potential of processed wood waste, the area of Poland and data on the price variability of biomass offered by sawmills, which are the first link of roundwood processing, were selected. This paper classifies price variability from the point of view of by-products that are the result of wood raw material processing.

The starting point for further analysis was a compilation of data on harvested and sold wood in Poland from 2010–2021 (Figure 1).

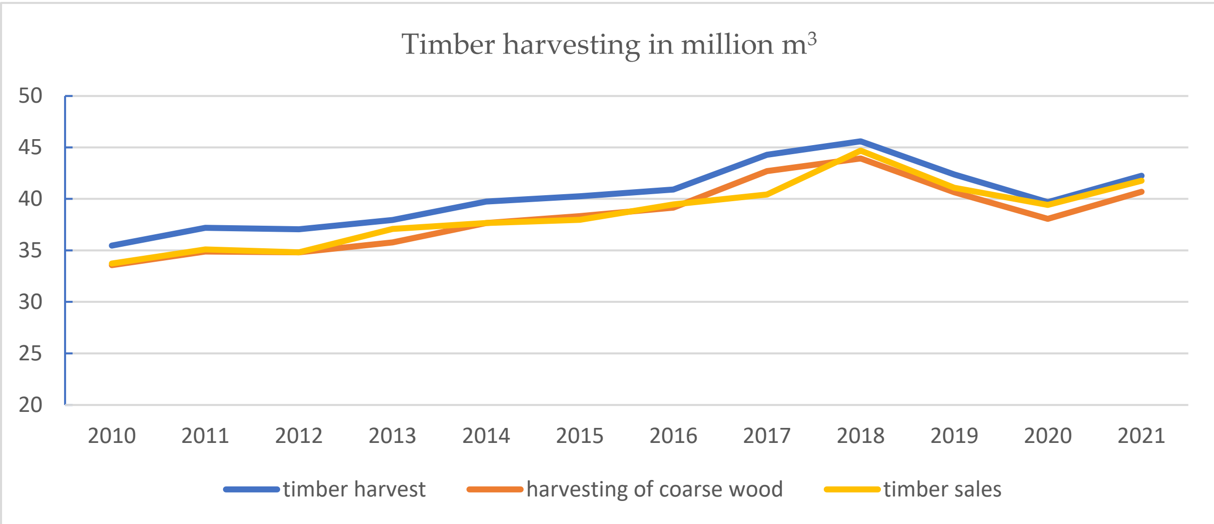

Figure 1. Timber harvest, sales, exports and imports from 2010–2021 [29–37].

Poland currently processes about 40 million m^3 of wood per year, of which sawmills process about 25 million m^3 [35]. The most popular and most processed wood raw material is pine. It accounts for about 61% of the processed raw material. The other species are as follows: spruce (6%), fir (4%), beech (7%), oak (6%), birch (5%) and others that account for a total of 11% [35]. Taking into account the volume of wood processing by sawmills, the destination for the resulting wood by-products of the so-called industrial wood biomass was indicated.

The profitability of processing wood by-products depends on a number of factors, including their quantity, form, market demand, transportation costs, external energy costs or the energy requirements of a given processing plant. The larger the sawmills, the greater the possibility of selling such by-products to, e.g., panel plants, or processing them into an energy product: pellets briquettes. In smaller sawmills, on the other hand, most often the by-product material is directly used for energy purposes. Thus, with the economic aspect in mind, it is important for further consideration to determine the demand of each group of sawmills. Using a model, it was possible to determine the processing structure of sawmills and indicate the amount of by-products they generate (Table 1) [29].

Table 1. Quantity of by-products from wood processing in sawmills in 2021.

Volume of Processing	Wood Consumption	By-Products					Total By-Products + Bark	Total By-Products + Bark Unit
		Total (40%)	Piecemeal Waste (30%)		Sawdust and Shavings (10%)	Bark (8%)		
			Woodchips (18%)	Other (12%)				
[thousand m^3]								
Total	16,515.75	6606.3	2573.1	2381.63	1651.58	1321.26	7927.56	1.30

Source: Own elaboration [29,38].

Timber prices are not the primary criterion regulating the amount of timber available on the market [32], but they are important in optimizing sales planning [39,40]. Information on changes in timber prices is a source of knowledge used in planning the activities of timber enterprises. Therefore, analyses explaining the mechanisms of timber market formation, through changes in the prices of wood by-products over time, are the subject of many studies both in Poland and in other countries [41–53]. These prices are under pressure from numerous political, natural and market factors. The functioning of the primary timber market, as well as the market for by-products of wood processing, is considered using time series [54,55]. The use of appropriate prediction methods allows us to predict changes in timber product prices [56–61]. Currently, most studies focus on the analysis of changes or trends in time series and their role in predicting market prices [62].

The purpose of this study was to confirm the applicability of time series predictive models and determine the fit of statistical methods to price changes in the industrial waste biomass market. It was hypothesized that the use of ARIMA and WH models makes it possible to predict wood prices over variable time horizons and adjust the price structure of wood processing products in accordance with changes in market demand.

2. Materials and Methods

In a group of numerous by-products from mechanical wood processing, the basic sorts traded on the market were included. Woodchip materials were singled out as the most valuable group and further divided into paper and lumber chips. Another group of analyzed biomass was sawdust and shavings from sawmill rework. The last form of by-product of roundwood processing was pine bark, which finds its position in the market for energy biomass and the product that goes directly to the market as horticultural bark. Data on the prices of wood by-products were obtained by verifying direct market prices and the literature data [63,64].

In order to verify the validity of predictive method selection, the Diebold–Mariano test was conducted. First, data up to September 2022 were considered, where the test answered a question of whether the fit of both models used differed significantly from each other. ARIMA and the multiplicative Winters–Holt (WH) model were selected [65,66].

To verify the price of wood by-products (industrial biomass), a predictive methodology was used, which includes in its assumptions an integrated autoregressive model with a moving average (ARIMA). In order to use ARIMA (p, d, q), the values of p, d and q must be estimated. These parameters indicate the following:

p is the autocorrelation parameter.

d is the integration level of the series.

q is the moving average parameter.

In general, ARIMA can be presented by the following Equation (1):

$$\varphi(B)\nabla^d z_t = \theta(B)a_t \; lub \; z_t = \sum_{i=0}^{p} \varnothing_i z_{t-1} + \alpha_t - \sum_{k=1}^{q} \theta_i a_{t-k} \quad (1)$$

where (2):

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p \quad (2)$$

We estimate the φ parameter to assess the impact of the previous value of the process on the current value (2).

This is a non-seasonal autoregressive parameter p (3).

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \quad (3)$$

This is the non-seasonal moving average parameter q and the parameter B as a backward shift operator, which can be written as (4):

$$B^p Z_t = Z_{t-p} \quad (4)$$

$\varphi_1, \varphi_2, \varphi_p \ldots$ and $\theta_1, \theta_2, \theta_q$ are unknown coefficients that were estimated from sample data using approximate probabilities.

In the equation $\nabla^d = (1-B)^d$, d is a backward shift operator of order "p", i.e., defined as (5):

$$\nabla Z_t = Z_t - Z_{t-1} \; along \; whit \; \nabla^d = \nabla \nabla^{d-1} \quad (5)$$

It is adopted as the first step of calculation to check the data integration. That is, determining whether the data are stationary or whether it is possible to transform them into the nature of stationarity. When the developed data are stationary, a parameter $d = 0$ is assumed, while when the data need to be transformed, the parameter $d > 0$ is adopted. To determine the stationarity of data, the KPSS (Kwiatkowski–Phillips–Schmidt–Shin) test was used [67]. This test verifies the hypothesis of whether the process is stationary determining whether consideration of differences is needed. While conducting the study of stationarity, the raw data is first subjected to test. The amount of differentiation process of the data is carried out until the data is characterized by stationarity after the KPSS test.

To determine the remaining parameters p and q, the autocorrelation function (ACF) and partial autocorrelation function (PACF) are used. Based on the resulting histograms, it is possible to proceed to the identification of the autocorrelation parameter and moving average. By comparing the histograms, the levels of increase in the value of obtained data in the adopted periods are determined, as is the probable variant of the ARIMA model. The methodological assumptions were in line with the authors' previous research papers [20]. In the conducted study, variants of parameters p, d and q were determined separately for each dataset of individual sorted groups.

In addition, a comparison was made with the Winters–Holt model. The WH is one of the prediction methods that uses exponential smoothing [68]. It involves the creation of an exponential smoothing moving average, the weights of which are determined according to the scheme that the older the data on the phenomenon under study, the smaller the value they present for a given prediction. Specific assumptions and equations are needed to develop the model.

Equation for random fluctuation estimation (6):

$$F_t = \alpha \times y_t + (1 - \alpha) \times (F_{t-1} + S_{t-1}) \quad (6)$$

where:

F_t—random variations for each observation in the time series.

y_t—observation value.

F_{t-1}—random changes for the previous observation in the time series.

S_{t-1}—estimated trend in the previous observation.

Equation for trend estimation (7):

$$S_t = \beta \times (F_t + F_{t-1}) + (1 - \beta) \times S_{t-1} \quad (7)$$

where α and β are model parameters with values between 0 and 1.

In model development, it is necessary to calculate expired predictions (8), i.e., for the period in which the actual value has already materialized, and then actual predictions can be calculated for the future period (9).

Equation for expired prediction (8):

$$y_t^* = F_{t-1} + S_{t-1} \tag{8}$$

Equation for actual prediction (9):

$$y_t^* = F_n + (T - n)\, S_n \tag{9}$$

where:

$T = n + 1, n + 2 \ldots.$

F_n—random variations for the last observation in the time series.

S_n—estimated trend in the last observation.

n—the number of observation.

The first values of F_1 and S_1 should be taken as:

$$F_1 = y_1$$

$$S_1 = 0$$

or

$$S_1 = y_2 - y_1$$

The next step in the analysis was to determine the correctness of the chosen methodology. Actual prices were compared with prediction prices.

R program version 4.2.0 of 2022 was the tool used to conduct the calculations.

The following equations were used: mean absolute error (MAE), mean absolute percent error (MAPE), and root-mean-square deviation (RMSE):

MAE (10):

$$\Delta x = |x - x_0| \tag{10}$$

where:

x—real value of price

x_0—prediction value of price

MAPE (11):

$$\delta = \frac{|x - x_0|}{x} * 100\% \tag{11}$$

RMSE (12):

$$RMSE = \sqrt{\frac{\sum |x - x_0|}{N}} \tag{12}$$

where N is the number of observation.

The final stage of study, using the Diebold–Mariano test, determined the accuracy of selected models for the October–December 2022 prediction period. This test answers the question of whether the difference in prediction efficiency is significant. The value for determining model fit and efficiency is the p-value, which is taken in advance at the level of 0.05.

In the prediction carried out, it should be noted that external factors such as inflation, economic crisis and historical prices have already been taken into account at the level of input data. The prediction also includes these factors in its data return value.

3. Results

Industrial biomass otherwise defined as a by-product of the technological process of wood processing is used most often for energy purposes or as a raw material for the production of wood-based panels. Releasing this biomass for sale allows its market price to be determined. The following is a graph showing the changes in the price of wood by-products by month from 2017 to 2022.

Figure 2 shows the price changes for individual groups qualifying as by-products of roundwood processing. The largest price increase occurred for sawdust and shavings, while the smallest change was for paper chips. Between 2017 and 2022, the price of paper chips increased by about 108%; lumber chips by about 116%; pine bark by about 112%; while the largest price increase of almost 167% was recorded for sawdust and shavings.

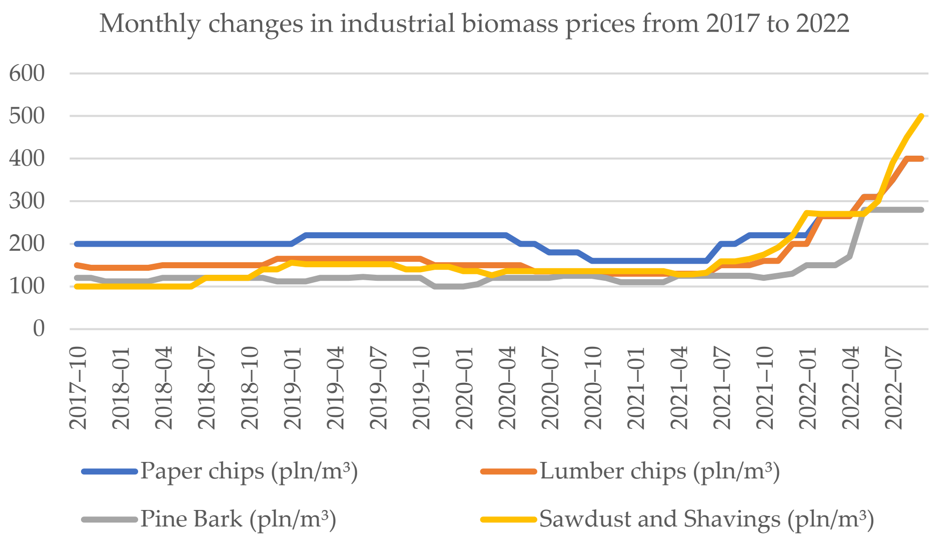

Figure 2. Monthly changes in industrial biomass prices from 2017 to 2022. Source: Own elaboration based on obtained data [33–38].

The Diebold–Mariano test was used to determine the fit of selected models. This test answers the question of whether the fit of both models used is significantly different from each other. In this case, it was hypothesized that WH has a better fit. Based on the results, it can be concluded that WH's fit based on data only up to September 2022 is better (Table 2). However, it should be taken into account that, as a result, both methods can have an equally good fit.

Table 2. Diebold–Mariano test results of ARIMA and WH fit.

Sorting	*p*-Value	Program R Confirmation
Paper chips	0.002385	Confirmed
Lumber chips	0.01342	Confirmed
Pine bark	0.1213	Confirmed
Sawdust and shavings	0.000472	Confirmed

Source: Own elaboration based on obtained data.

After data analysis, the corresponding ARIMA variants were selected (Table 3).

Table 3. Selection of ARIMA variants for paper chips, lumber chips, pine bark, sawdust and shavings.

Sorting	Variant of Model ARIMA
Paper chips	2, 2, 0
Lumber chips	5, 2, 0
Pine bark	0, 1, 0
Sawdust and shavings	1, 2, 3

Source: Own elaboration based on obtained data.

3.1. Prediction for Paper Chips

Table 4 shows the values of the forecast using ARIMA and WH compared to the actual price. As you can see in the case of paper chips, better values are achieved when using WH. The smallest differences between the actual and forecast prices were recorded for the first month of forecasting (October). The biggest difference occurs for the last forecast month (December). The WH method gives better results in the short-term forecasting period (for one month prediction).

Table 4. Paper chip price prediction for October–December 2022.

	ARIMA		Winters–Holt
	Actual Price (pln/m^3)	**Predicted Price (pln/m^3)**	**Predicted Price (pln/m^3)**
October 2022	400	444.27	426.25
November 2022	400	475.68	446.87
December 2022	370	491.78	463.93

Source: Own elaboration based on obtained data [33–38].

3.2. Prediction for Lumber Chips

Table 5 shows the predicted value for lumber chips. The use of WH gives smaller differences between the forecast and the actual price compared to ARIMA. The smallest errors were recorded in the first month of forecasting (October), and the largest for the last month (December). The WH method gives better results in the short-term forecasting period (for one month prediction).

Table 5. Lumber wood chip price prediction for October–December 2022.

	ARIMA		Winters–Holt
	Actual Price (pln/m^3)	**Predicted Price (pln/m^3)**	**Predicted Price (pln/m^3)**
October 2022	400	446.56	414.87
November 2022	400	463.49	415.97
December 2022	350	480.41	454.12

Source: Own elaboration based on obtained data [33–38].

3.3. Prediction for Pine Bark

Table 6 shows the differences between the actual and forecast prices on the pine bark example. In this case, the constant difference in each month of forecasting was recorded using ARIMA and amounted to PLN 20/m^3. With the WH method, the smallest difference was recorded in the second month of forecasting, and the largest in the third month of forecasting. The ARIMA method gives better results in the longest-term forecasting period (for three months prediction).

Table 6. Pine bark price prediction for the period from October–December 2022.

	ARIMA		Winters–Holt
	Actual Price (pln/m^3)	**Predicted Price (pln/m^3)**	**Predicted Price (pln/m^3)**
October 2022	300	280	281.51
November 2022	300	280	271.45
December 2022	300	280	257.60

Source: Own elaboration based on obtained data [33–38].

3.4. Prediction for Sawdust and Shavings

In the case of sawdust (Table 7), the smallest differences between the actual and forecast prices were recorded for ARIMA for the two forecast months (October, November), while the largest ones were observed in the third month of forecasting (December). WH had the smallest differences in the second month of forecasting (November), where the largest differences were for the first and third months of forecasting (October and December). The ARIMA method gives better results in the longest-term forecasting period (for two months prediction).

Table 7. Sawdust and shavings price prediction.

	ARIMA		Winters–Holt
	Actual Price (pln/m^3)	**Predicted Price (pln/m^3)**	**Predicted Price (pln/m^3)**
October 2022	550	536.53	472.18
November 2022	550	577.13	498.45
December 2022	450	607.29	545.45

Source: Own elaboration based on obtained data [33–38].

3.5. Summary

The actual and predicted prices were compared to identify the errors that resulted from the prediction method used, and their level was determined.

The error comparison for both methods shows the variation in results (Tables 8 and 9). The RMSEs obtained using two methods are very similar, i.e., it can be concluded that the methods provide similar prediction efficiency. The methods used overestimated the forecast values. In the case of pine bark and sawdust and shavings, the forecasted prices were lower than the real prices. The RMSE is based on the exponentiation operation. As a result, it is much more prone to impose larger penalties with larger differences between the predicted values and the actual values. It is also related to the sensitivity of this measure to outliers. On the other hand, the MAE, being the average of the absolute values of the prediction errors, is more intuitive, but also gentler in situations where the difference between the predicted and the actual value is large. It can therefore be concluded that the best model selected using the RMSE value is the model that was able to better predict the values of the set's outliers. On the other hand, looking through the MAE analysis and guided by the average of the absolute error values, the selected model is generally able to correctly predict price values, but it may make larger errors when outliers occur.

Table 8. Summary of MAE, MAPE and RMSE for the prediction using ARIMA.

	Paper Chips			Lumber Chips			Pine Bark			Sawdust and Shavings		
	MAE	**MAPE [%]**	**RMSE**	**MAE**	**MAPE [%]**	**RMSE**	**MAE**	**MAPE [%]**	**RMSE**	**MAE**	**MAPE [%]**	**RMSE**
October 2022	44.27	11.07	6.65	46.56	11.64	3.41	20	6.67	4.47	13.47	2.45	3.67
November 2022	75.68	18.92	8.70	63.49	15.87	3.98	20	6.67	4.47	27.13	4.93	5.21
December 2022	121.78	32.91	11.04	130.41	37.26	6.10	20	6.67	4.47	157.29	34.95	12.54

Table 9. Summary of MAE, MAPE and RMSE for the prediction using WH.

	Paper Chips			Lumber Chips			Pine Bark			Sawdust and Shavings		
	MAE	**MAPE [%]**	**RMSE**	**MAE**	**MAPE [%]**	**RMSE**	**MAE**	**MAPE [%]**	**RMSE**	**MAE**	**MAPE [%]**	**RMSE**
October 2022	26.25	6.56	5.12	14.87	3.72	3.86	18.49	6.16	4.30	77.82	14.15	8.82
November 2022	46.87	11.72	6.85	15.97	3.99	4.00	28.55	9.52	5.34	51.55	9.37	7.18
December 2022	93.93	25.39	9.69	104.12	29.75	10.20	42.4	14.13	6.51	95.45	21.21	9.77

The Diebold–Mariano accuracy test for the October–December 2022 period provides results that can be interpreted as the significance of prediction efficiency. In observing the prediction results and the fact that *p*-value is high, it can be concluded that WH does not have better efficiency than ARIMA (Table 10). This does not necessarily mean that its prediction efficiency is worse.

Table 10. Diebold–Mariano test results of the prediction efficiency of ARIMA and WH.

Sorting	*p*-Value	Program R Confirmation
Paper chips	0.05951	Confirmation
Lumber chips	0.04165	Confirmation
Pine bark	0.8471	Confirmation
Sawdust and shavings	0.3655	Confirmation

4. Disscusion

Price fluctuations due to market, natural conditions and organizational conditions [69,70] are one of the main sources of uncertainty in economic planning [40,55]. Hence, the stability and predictability of the market is an incentive for investors with regard to investment decisions for the development of a particular industry. Knowledge of the causes of price fluctuations and trends is the basis for a deep understanding of the system mechanisms and development trends of related research fields [71]. Identification of factors influencing price formation, as well as the ability to implement them in economic planning, becomes an essential condition for the survival of business entities in the current volatile environment. Price prediction is one of the basic instruments for supporting decision-making processes in the economy. Therefore, knowledge of market prices, in this case the price of forest biomass, seems to benefit both suppliers and buyers of wood raw material [72].

Prices of harvested wood by-product assortments are shaped by many market factors. Observed technological changes and regulatory adjustments, as well as increasing optimization of wood utilization, are the main factors influencing fluctuations in the wood products trade [73]. In most cases, the change in prices of wood processing by-products is caused by an increase in demand for both cellulose and biomass energy materials. In the future, the industrial biomass utilization sector may gain importance due to the interest and consumption of renewable biomass sources. Based on studies [74], this is influenced by EU policies [75] regarding the market for firewood and industrial wood (pulp and paper industry). At the same time, for proper economic planning, it is necessary to have knowledge of, among others, changes in the markets. One of the key elements of this process is the prediction of timber prices. The solution to the problems of price changes in the timber market can be the development of monitoring of the timber customer market in the country and in the European and world markets by evaluating the level of trade in by-products of wood processing, reviewing prices at the appropriate frequency and responding to these changes. Price prediction is one of the elements of demand evaluation by timber producers in the near future, and support with modeling can be a valuable economic tool [76]. Taking this into account, it is justifiable to undertake efforts aimed at revealing prediction methods that allow the building of predictions that best match the reality shaped by the above-mentioned variables.

In predictive analyses of price changes, it is necessary to focus on new sectors of timber industry activity (paper production, lumber trade, biomass as a renewable energy source). The timber industry [77] operates based on market factors that shape supply and demand in the primary timber market. Differences in the cyclicality of price changes between different products (woodchips, sawdust and bark) are largely due to product demand [78]. Changes in market preferences determine long-term trends in the industrial products sector. The cyclical nature of pricing patterns for industrial biomass is related to the condition of the European economy responsible for overall fluctuations in timber prices. From 2018 to 2022, there have been dynamic economic changes due to an increase in the supply of roundwood and its products. It is possible to notice fluctuations that revealed large increases in the prices of wood biomass in Poland by as much as PLN 200–350/m^3 in the case of the paper or lumber chip sort in 2018–2022; for the sawdust and shavings sort, it was as high as

PLN 375/m^3 [63,64]. After recent years of stable price increases, significant changes in demand translated into a sharp increase in prices starting in the second quarter of 2022. The situation in the European timber market was also related to the phases of the global economic cycle. The increase in the price of wood by-products in European countries in 2022 was due to the energy crisis. In the first and fourth quarters of 2022, there was an increase in selling prices. The fluctuations in prices coincided with the peak in the Polish timber economy due to rising demand from the construction sector. However, demand for wood processing by-product sorts in Poland was particularly dominated by solid fuel shortages. In this situation, research verifying the feasibility of using various methods to identify future market changes, including price, is particularly important.

The price of bark resulting from its supply (both quantity and assortment structure) depends primarily on the seasonality of demand in the horticultural area and the stable level of supply to customers. Studies have confirmed high price stability for bark supply both in Poland and Europe [79]. According to the research, the price and supply of woodchips and sawdust, as well as wood shavings, is an effect of both market and non-market factors, depending on the products and geographic region [80]. Wood biomass (chips, sawdust, shavings), which is a by-product of industrial processing, shows higher price elasticity than bark [81], suggesting that price changes have less impact on the supply of industrial biomass from sawmill wood processing [82,83]. Analyses carried out using prediction models [46,54,84,85] and, in the case under review, using the ARIMA model, which is popular for forest resource evaluation, and WH [21,55,68,86,87] confirmed the occurrence of projected increases in bark prices at an overall level of 6%. Comparing the deviations for 2018–2022 (projected), while the other woodchip sorts significantly deviated from the acceptable level, exceeding 10%, in the case of sawdust and bark, the increases in deviations of projected prices in 2022 were significant (−35%). The largest increase in prices was found in the case of assortments such as woodchips at the end of the third and the beginning of the sixth quarter in 2022 (Figure 2). The scale of monthly measurements only slightly ensures predictability of revenues, limiting the possibility of making economic decisions during the year. The analysis of information using the autocorrelation of prices of individual wood industry by-products allows us to illustrate the seasonality for the studied assortments. Such a situation can be observed in the case of sawdust sort, which increased its price in the winter months of 2022. This also causes an increase in the price of fuel products for individual customers supplied by suppliers representing the timber industry. At this point, it can be observed that other wood sorts also have a seasonal characteristic.

One of the commonly used methods for change prediction is ARIMA. Diego R. Broz [85] claims that this method usually provides highly satisfactory fits with low data collection costs. On the other hand, this type of model shows poor results in long-term prediction and predicting unusual movements [88]. Taking this into account, it was decided to verify the usefulness of this method for predicting prices for the analyzed wood assortments. Based on this research, it was found that the application of ARIMA for paper and lumber chip prices under market uncertainty showed large deviations of prediction results from actual results. The MAPE for ARIMA was found to be larger than that for WH. The deviations found for ARIMA, on the order of 20% (Tables 7–9), may fluctuate further within the operations of timber companies in 2023 and beyond, which is a result of, among others, rapid changes in energy biomass prices. Rapid declines, often caused by market factors, in such wide ranges can be difficult to identify. In the studied time horizon of 2017–2022, irregular fluctuations in prediction price changes for wood processing by-products were an uncertain part of the analyzed data. The nature of strong market disturbances (including political ones) significantly affected the price of assortments.

This is also the result of changes in the price of wood raw material traded between the Polish and Western European markets on the one hand, and the Baltic and Scandinavian markets on the other [89]. The intensification of the energy crisis in Central Europe has led to an increase in investments using renewable energy sources (RES). Measures to ensure access to thermal energy as well as electricity have shifted price fluctuations (increases) to sorted groups that can be used to generate thermal energy (forest biomass and wood by-products of mechanical processing), thus relieving the use of fossil fuels. The popularization of low-quality biomass use is fostered by the founding of the New Green Deal [75], which defines the use of woody biomass with a reduction in the harvesting of forest biomass. Changes in the price level of woody biomass play a huge role in planning the cost of its purchase. This is especially important given the situation on the eastern side of Poland. Some of the largest suppliers of wood residues were Eastern European countries, i.e., Ukraine, Russia and Belarus [90]. Reduced resources by the suspension of imports from Eastern countries is one of the reasons for increased prices of wood raw materials intended for biomass purposes.

5. Conclusions

Over the studied time horizon, the prices of products under study show a strong upward trend both in terms of direction and broad amplitude of change (Figure 2). Verification of the adopted monthly time series was used to analyze the overall variability of price components depending on the parameter causing the price fluctuation and the time horizon of change.

Both ARIMA and WH showed that the quality of obtained predictions decreased within the period for which the prediction was made. On the basis of research conducted, both methods can be recommended for predicting the future price up to one month in advance. In addition, it was found that the periodic deviation of prediction price levels from the actual ones occurring in the time horizons studied (months, quarters) is unstable.

Seasonal fluctuations in the price of by-products occurring in the annual horizon are related to the seasonality of demand sourcing for energy wood. Seasonality was characterized by assortments such as woodchips and sawdust. For pine bark, strong seasonality in price changes was not found. Price patterns depend on the sorting of wood processing by-products.

Analysis of the overall volatility of timber prices and supply allows for the use of ARIMA and WH in predicting timber prices and planning the amount of timber to be harvested in short time horizons by adjusting the assortment structure of wood processing by-products to changes in market demand. The hypothesis that ARIMA and WH models can be used to forecast biomass market prices was confirmed.

Long-term price changes, on the other hand, require prediction with higher measurement frequency or the use of models such as WH and ARIMA in short-term evaluations. In the long term, increasing demand for timber will result in a gradual increase in prices, which is not consistent with the indications made in the modeled example. Further research requires the introduction of new models to determine the impact of changes on the prediction of prices of wood by-products in both Poland and other European countries.

The conclusion of a comparison between ARIMA and WH is to fit the method to the market conditions of a given sort. In the case of sawdust and wood chips and pine bark, where they are characterized by seasonality, ARIMA is a better fit for the prediction model, while in the case of lumber and paper chips, which are stable in the market, WH is a better prediction model. However, the authors tend to verify ARIMA and WH in a weekly time series. The practical aspect of study results was to determine the usefulness of both models for the correct forecasting of industrial biomass prices depending on the relevant market conditions of the given assortments.

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