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Unlocking the potential of surplus food: A blockchain approach to enhance equitable distribution and address food insecurity in Italy

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ABSTRACT

Food insecurity and food surplus are two pressing issues that have been exacerbated by the COVID-19 pandemic. This paper presents a novel approach to addressing these problems using blockchain technology. More specifically, data from the Italian Regusto platform are analysed to identify factors that determine the volume and economic value of surplus food redistribution.

From a methodological statistical perspective, the performance of Stepwise Multiple Linear Regression and Random Forest are compared in a blockchain data analysis. The effective machine-learning-based analysis reveals that the Regusto platform gives people greater access to the surplus food redistributed by non-profit organizations and suppliers through both donations and sales. The study also highlights the potential effects of redistributing surplus food on the beneficiaries' diets and health and we find that redistributing surplus food can reduce household food insecurity among low-income families and communities measured by food poverty and COVID-19 indexes at different spatial locations.

Overall, by offering a unique perspective on these issues through the lens of blockchain technology, our study can inspire further research on how this technology can ensure everyone has enough affordable, nutritious food to lead healthy lives.

1. Introduction[1]

Daily access to food is a basic human need [1] while hunger is still a critical global issue that affects over 10% of the entire human race [2]. Within this framework, food insecurity and food surplus are controversial and concurrent social issues, especially in high-income countries, with a double implication. On one hand, poor access to healthy, safe, and affordable food puts the lives of individuals, families, and communities at risk. The situation has become even more serious in areas suffering from extreme poverty impacted by the COVID-19 pandemic and due to the indirect effects of the war in Ukraine [3]. 8.3% of the European population was under the pressure of food insecurity in 2016, meanwhile, the percentage of individuals reporting a similar level of difficulty in Italy reached 13.4% in Italy as of 2017 [4,5]. On the other hand, a staggering percentage of the food produced is lost or wasted, which has a profound impact on economies, societies, and the environment. In Europe, food waste is a bigger issue than food loss. Food prepared but not consumed due to inappropriate planning and failure to meet customers' needs is commonly referred to as food surplus which is edible and valuable [4].

Harnessing surplus food to solve the issue of food insecurity rather than letting good food go to waste could be a win-win strategy, that befits the circular economy model and the European Circular Economy Action Plans for which redistribution and reuse are the primary goals ([6–8,41]).

Over the last few years, much research has been carried out on the various stages of FSCM and the CE framework ([7,41]). Some studies have focused on converting FW into energy while others have focused on food sharing practices and models to reduce FLW ([9]; Sarti et al., 2017) and surplus food redistribution through food banks and food aid supply

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chains [10–13]. Positive results have been observed, and food surplus has become the main source of charitable food aid [14]. Obstacles emerge with the continuous studies carried out by other authors. Food redistribution via charity activities is questioned as a "double blade" – facilitating charitable food flow and reducing food designed for disposal, meanwhile, compromising dietary health and leading to nutritional poverty as part of food insecurity. Lack of fruits, vegetables, and dairy products has been pointed out [15]. As Toti et al. (2016) ([43]), the negative effects of food redistribution through food banks and charity organizations are summarised as three unintended consequences.

- The exclusion of end beneficiaries who are left with limited choices;
- The intention of "zero disposal" outweighs the willingness of providing charitable food for redistribution and prevention of food waste;
- The rise of health and ecological costs due to excess consumption of energy-dense food and metabolic food waste.

Messner (2020) and Summet et al. (2017) suggested further study on the structural nature of food surplus production and over-consumption, and combining food security and nutritional poverty when handling food insecurity issues with charitable food redistribution. A recent research strand has focused on the use of digital technologies to improve food management, reduce or prevent food waste and contribute to sustainable supply chains [16], which would have positive economic and environmental impacts on the economy and society [9,17–19] and therefore reduce the lack of digital logistical infrastructure [20].

Blockchain leverages a decentralized structure to support a peer-to-peer network which facilitates data flow. It is perceived as an innovative attribute to data security, data transparency, and data efficiency; therefore, it has gained a grounded reputation in promoting sustainable global supply chains [21]. Blockchain is a promising technology of our digital revolution as it has numerous platforms that address the FW problem with economically-viable business models [22,23]. Most of them provide transparency and traceability of food information across the global FSC, which is of particular benefit to food safety and integrity [24]. Each actor in FSC provides full details of the origin of their food products, while environmental monitoring data are integrated during distribution. As a result, each FSC actor can easily access up-to-date and reliable product information and improve their food safety knowledge. Kayikci et al. [25] proposed the use of blockchain technology to promote food journey traceability: by relying on smart contracts between supply chain members, it is easier to trace products back to the origin in the case of food contamination, thus detecting the illness source and ensuring that other food is discarded if it was in contact with contaminated ingredients. Information collected can also be made accessible at the customer level so that customers can trace the origin of purchased products. In addition, blockchain technology benefits the elimination of communication barriers among various actors in the food supply chain which, at the same time, play the main roles in food redistribution and food waste reduction [26]. However, the effects of blockchain technology on FLW reduction or prevention seem often indirectly linked to the primary goal of better product transparency and traceability. Blockchain technology was recognized as the critical success factor for a sustainable supply chain by preventing FLW at many stages of the supply chain, for instance through advanced product transportation and inventory management and facilitating real-time order placement and automation of production tasks through smart contracts (Yontar et al., 2020; [27]).

Regusto, one of the digital tools cited by Strotmann et al. [28], relies on blockchain technology to track the transactions of donated food products, meanwhile ensuring greater transparency and easier data management. As a practical example in Italy, it aims to reduce food waste and increase food surplus redistribution to the most vulnerable communities. On Regusto's platform, food supply chain members such as supermarkets, grocery shops, and farms are engaging closely with NPOs such as Caritas and food banks, which help disadvantaged people affected by hunger and food scarcity [29].

Regusto[1] claims that on the platform, every month over 200 tons of food and non-food goods are donated and sold which is equivalent to 22,238,594 meals distributed in the social perspective, 17,133,634 Kg CO_2 emission reduced, and 21,126,664 m^3 water saved in the environmental perspective.

By providing a unique framework of analysis linking food insecurity, food surplus and blockchain technology, this paper aims to examine the factors that determine the value and volume (quantity) of the transactions recorded on the Regusto platform between February 2021 and January 2022. According to this perspective and bearing in mind the harmful impacts of poverty and the need to address food insecurity in Italy ([30]; [42]) our study also aims the roles that the heterogeneous spatial distribution of food insecurity and the COVID-19 pandemic have played in determining financial transaction flows in Italy.

From a methodological perspective, the paper contributes to blockchain performance evaluation using a machine learning-based model instead of a traditional linear regression model.

From an applied perspective, this paper helps to verify and validate the effectiveness of digital platforms in the efficient use of resources, thus implementing the principles of circular economy, but at the same time considering the reuse of resources and surplus food with their further and specific (still) economic destination, thus making entrepreneurs perceive their potential and value as well.

The remainder of this paper is structured as follows. Sections 2.1. and 2.2 include details of our dataset, background information on the Regusto platform and a descriptive analysis. The methodology, estimation results and analysis are described in Section 2.3 and Section 3, which also include a description of a clustering approach (Section 3.3-3.4). Section 4 provides information on implementation models and approaches, discusses the findings and limitations of the study and provides suggestions for future research.

2. Materials and methods

In this section, the dataset for our regression analysis and the models is described. Firstly, two different model specifications were determined (Spec). Without loss of generality, the first considers the transaction volume as the response variable y_{volume}, (hereafter referred to as Spec.1) and the second uses economic value as the response variable $y_{economic\ value}$ (hereafter referred to as Spec.2) which will be explained in detail in the next sections. By comparing SMLR and RF models, we can identify the best fitting model and unfold the influencing factors.

2.1. Background: Regusto blockchain platform

The Regusto platform was created by the start-up Recuperiamo s.r.l. in 2016 with the aim of reducing FW and increasing SFR to those in need. The platform acts as an intermediary and marketplace to save good food from going to waste and redistribute it to frontline charities, companies and NPOs. Regusto now also offers other non-food products such as electronics. Regusto uses blockchain technology to monitor the value and volume of each transaction, which may have social and environmental impacts.

Blockchain technology, the backbone of the Regusto platform, enables secure transactions and supply chain transparency. B2NPO transaction data was obtained for conducting a demand and supply analysis of local communities. Traditionally, B2NPO marketing challenges came from the lack of transparency on donated goods. The category and the quantity of the goods remained unknown until they arrived at destinations specified by NPOs and charities [31]. With Blockchain technology beneficiary agencies know what they are going to receive as they can track all the information about the food donated on the Regusto

[1] https://regusto.eu/.

platform. Socially, Blockchain technology has increased the recovery and redistribution of surplus food, and food donations to vulnerable people and raised awareness of food insecurity and FW in our society [9]. Economically, by donating surplus food, companies are able to save raw materials and production, storage and packaging costs and are entitled to tax relief for their donations made to charities. Environmentally, Regusto has achieved impressive results. By June 2022, Regusto had saved over 2.2 mln meals from landfills and avoided 4.3 mln m^3 of water waste and 340,000 Kg of CO_2 emissions.

2.2. The constructed dataset and the descriptive analysis

In this paper, only food transactions recorded on the Regusto platform have been taken into consideration to gain insights on surplus food redistribution and food waste reduction. 866 transactions occurred between February 2021 and January 2022, which were classified as donations or sales, constructed the final dataset. After data cleaning, each transaction came with its volume (Kg), economic value, transaction date, locations of the buyers/beneficiaries and the sellers/donors (hereafter known as buyers and sellers respectively in the following paragraphs), macro category of the transacted object(s), and the Kg of CO_2 emission saved which was converted from the saved FW. However, the fact that the Kg of CO_2 emission saved was only related to the donations. Therefore, this factor was dropped to avoid data inconsistency. The macro categories were, pasta (macro-category1), dairy (macro-category2), meat (macro-category3), dessert (macro-category4), legumes (macro-category5), baby food (macro-category6), canned food (macro-category7), food basket (macro-category8), frozen food (macro-category9), eggs (macro-category10), fruit and vegetables (macro-category11) and NEC (macro-category12) which was not classified in the other macro categories.

Donation and sales transactions were not distributed equally over the months due to seasonal events, for instance in December, donation transactions experienced a significant increase. However, due to the small sample size, the analysis was carried out with the two types of transactions combined. To handle the zero economic value of a donation transaction, we assign the mean value of each macro category to the donated food items. The sample represented an average of 403.7 Kg of food items "traded" by each transaction on Regusto's platform over the whole observed period. On average, each transaction created around 2100 euros in value. The average distance measured reached nearly 80 Km.

In the observed period, transactions were not evenly distributed over the months (Fig. 1a). Furthermore, over 30% was generated in December, while August had the lowest transaction (around 2.5%). In a week, the volume of the daily transactions displayed a significant difference between the weekdays (at least 9% as of Friday's frequency) and the weekends (around 3.5% of Saturdays and Sundays) as shown in Fig. 1b.

Legumes, meat, and pasta were the top 3 macro categories with the highest count of the generated transactions (Fig. 1c). Their combined transactions represented 30% of the total number. However, fruit and vegetables (1.73%) represented the least.

In our dataset, we had NPO associations as buyers from 24 different provinces of Italy (Fig. 1d). On the contract, the sellers were supermarkets, farms, and grocery stores from 27 different provinces (Fig. 1e). In Fig. 1f, we got a general blueprint of how the food goods moved from the sellers to the buyers. Some happened within the region, others happened despite a long distance.

We introduced four new variables, which are COVID index (the number of COVID cases per 1000 inhabitants per day) per buyers' and sellers' provinces, FPI of the counterparties' provinces respectively [32]. Food poverty identifies people who are at risk of not having enough access to nutritious food to sustain a healthy life [33]. FPI represents the percentage of the population at risk of food poverty in each province of Italy. According to Marchetti and Secondi, FPI is calculated by setting up a food poverty line at 60% of the median equivalent food consumption expenditure at the provincial level.

2.3. Modelling blockchain transactions

Transaction volume and the responding economic value are the two target variables in the quantitative analysis, which results disclose potentially the effects of surplus food redistribution by Regusto's

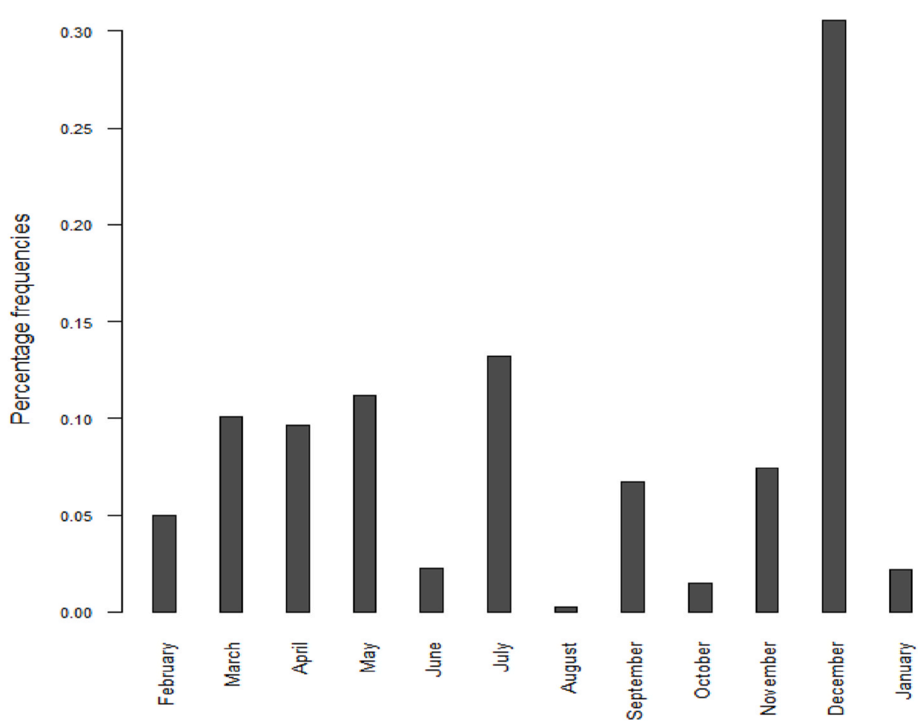

Fig. 1a. Percentage frequencies of the transactions in Kg per months.

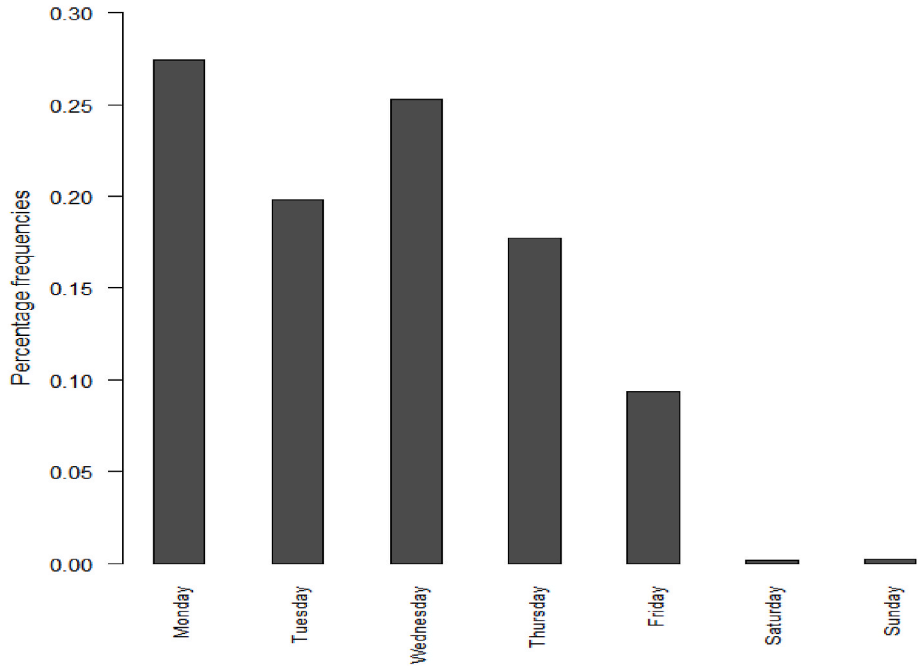

Fig. 1b. Percentage frequencies of the transactions in Kg per days in a week.

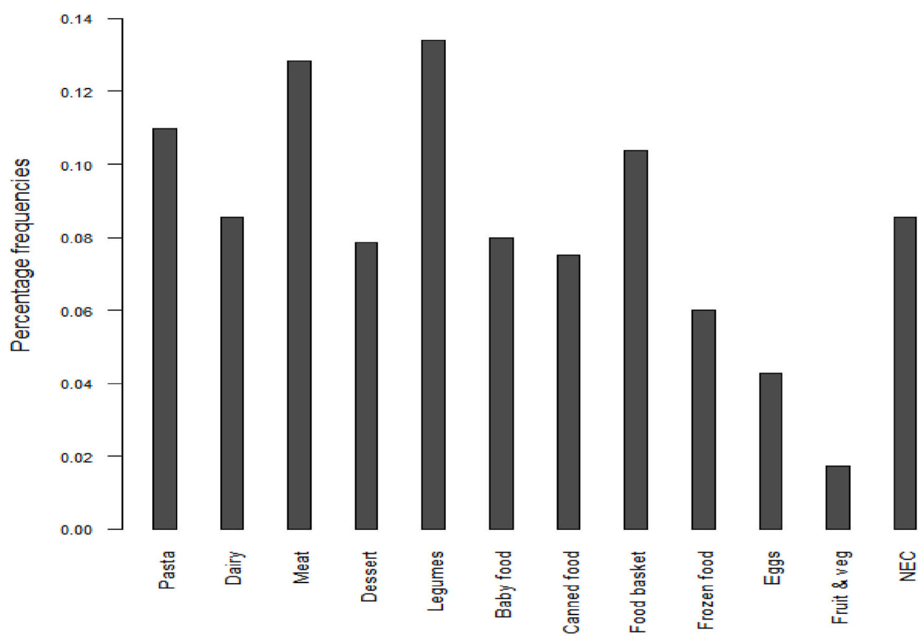

Fig. 1c. Percentage frequencies of the transactions by macro categories in the observed period.

platform with blockchain technology and the driving factors for success or failure. However, we must handle the combined issue of multiple explanatory variables and a relatively small sample size. In this case, we implemented the forward Stepwise regression model for its proven advantage in variable selection [34] under the condition of parameters. Breiman [35] remarked a random forest is an effective tool in prediction and classification, and a competitive mechanism considered a Bayesian procedure. Therefore, we carried out our quantitative analysis by leveraging both methods followed by a comparison of the robustness test results for the best-fitted model.

2.3.1. *The forward stepwise regression approach*

The forward Stepwise regression is a classic and well-known test-based approach to build a regression model with all the statistically significant variables [34]. Starting with an intercept only model without the predictor variables, variables are introduced one by one at each forwarding step, guided by a certain criterion. We choose Akaike information criterion here to compose our final regression models.

In the modelling process of our two equations, we assume the volume of the transactions as the response variable of Spec.1, and the explanatory variables are distances, days of the week, the months, FPIs of the provinces from where the buyers and sellers are, the macro categories, and COVID index of the buyers' and sellers' provinces. We assume the economic value of the transactions as the response variable in Spec.2, while the explanatory variables include all mentioned in Spec.1 and the transaction volume.

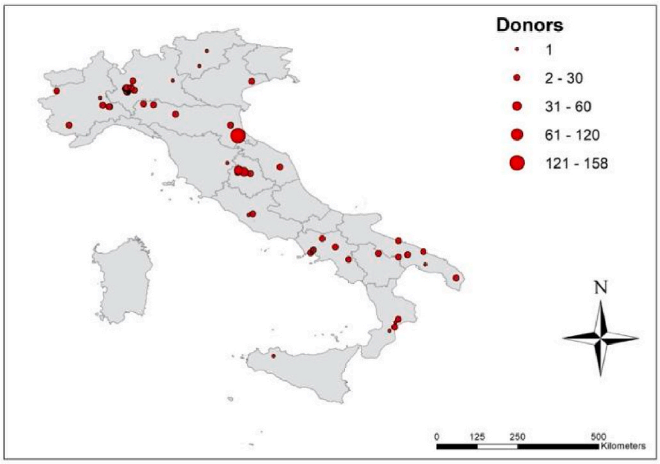

Fig. 1d. Locations of sellers (in red).

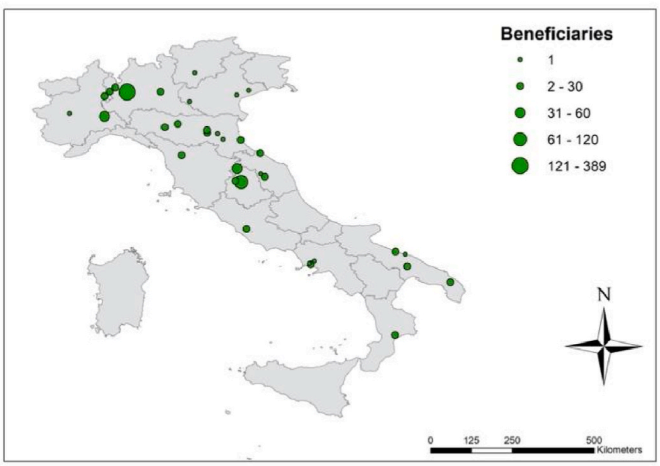

Fig. 1e. Locations of buyers (in green).

2.3.2. *The random forest approach*

We refer to the RF model among the machine learning algorithms. RF is a machine learning non-parametric model that can be used for regression, classification, and forecasting. It is used to identify the patterns hidden in the traditional regression models such as the linear and generalised linear regressions [35]. It also decreases the errors by minimizing the prediction variance while maintaining the bias, which tells the difference between the model prediction and the real value of the target variable. The regression tree architecture is the backbone of this machine leaning technique. Each tree is built from a combination of the predictor variables which are not overlapping in other trees. The algorithm provides the same prediction for all observations in one tree and therefore results in the mean of the response value of that tree. Fundamentally, this algorithm runs to achieve the best result by minimizing the Residual Sum of Squares.

Proposed by Breiman, bagging aggregation technique combines the bootstrap with the randomization of the input variables to separate the trees. Thus, instead of making the best split among all predictor variables, it creates a random subset of k variables for each tree first and then makes a further split. This approach increases the accuracy by reducing the bias [35,36]. Therefore, denoting the number of bootstrap samples by B and the decision tree estimator developed on the sample $b \in B$ by $f^{tree}\ (X|b)$, the RF estimator is defined as follows:

$$f^{RF} = \frac{1}{B}\sum_{b=1}^{B} f^{tree}(X|b) \tag{1}$$

Where $X = (X_1, X_2, \ldots, X_n)$ is the vector of predictors on the sample b. To obtain a RF model with the proper parameter, which combines the number of trees and number of variables under one tree, we run a tuning parameter test by splitting our dataset to train set (80% of the dataset) and test set (20% of dataset). The test result showed that Spec.1 composed of 500 trees the number of variables that must be considered in each tree was 6 (RMSE = 1086.454), while the number of trees increased to 1500 and the number of variables that must be considered was decreased to 6 (RMSE = 4574.831) for Spec.2.

To highlight the potentially important independent variables in our RF model, we measure the variable importance which represents the relative influence of each predictor variables. It is measured with the number of times a predictor variable is selected to trigger the split

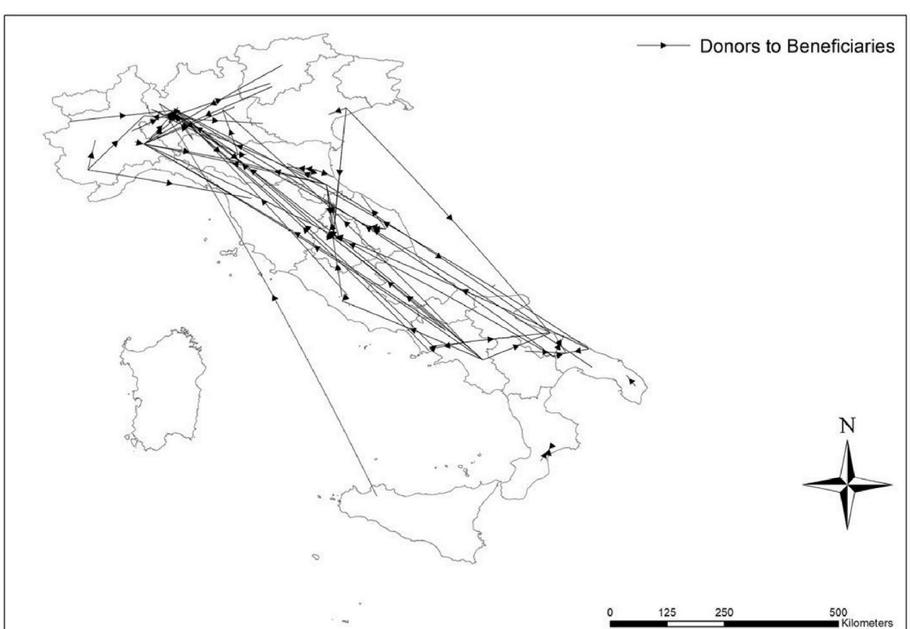

Fig. 1f. Transactions from sellers to buyers.

during the tree building process, weighted by the squared error improvement to the model after each split, and averaged over all trees. Breiman proposed a weighted impurity measure for the variable importance, for all nodes t averaged over all N_t trees. To calculate, we refer to the Gini importance, obtained by assigning the Gini index to the impurity *i(t)* index [35,36]. This measure is denoted here by IncNodePurity:

$$IncNodePurity(X_i) = \frac{1}{N_T}\sum_T \sum_{t\epsilon T:v(s_t)=X_i} p(t)\Delta i(s_t, t, t_l, t_r) \tag{2}$$

where $v(s_t)$ is the variable used in split s_t, $p(t)=\frac{N_t}{N}$ the proportion of samples reaching t, N is the sample size and $\Delta i(s_t, t, t_l, t_r)$ is the impurity decrease of a binary split s_t dividing node t into a left node t_l and a right node t_r:

$$\Delta i(s_t, t, t_l, t_r) = i(t) - \frac{N_{t_l}}{N_t} * i(t_l) - \frac{N_{t_r}}{N_t} * i(t_r) \tag{3}$$

The *IncNodePurity* (X_i) provides the importance of feature X_i, which takes the number of splits enclosing the variable into account.

3. Data analysis

3.1. The forward stepwise regression model

With Spec.1, the best model presents an adjusted R-square value of 0.2405 with the statistically significant variables shown in Table 1.

The FPI of the buyers' provinces is directly related to the volume of transactions. It shows a positive result of Regusto's platform facilitating the food stock to those provinces with the greatest food poverty problems. On the opposite side, the FPI of the sellers' provinces has a negative relation with the transaction volume. In other words, the provinces with the least food poverty problems give away the most volume.

The distances between the provinces of the two counterparties (in kilometres) positively influence the quantity exchanged. About the macro categories of the goods in the transactions, categories with a significant positive relation are fruit and vegetables, food basket, legumes, followed by baby food, canned food, and dairy. Interestingly, fruit-and-vegetables is a macro category with the lowest counts of transactions.

Furthermore, with respect to the days in a week, the model shows a negative relation of Friday with the Kg exchanged, which has a positive relation with Wednesday. In a year, February, December, and July present a positive relation with the volume.

COVID index is statistically significant, but only of the buyers' provinces. When there is a lighter impact of COVID on the day before the transactions in the buyers' provinces, the transaction volume turns out to be greater.

With Spec.2, the model with the best AIC has an adjusted R-square value of 0.4473 and we acquired the information as shown in Table 2.

The variables that quantify the COVID impact are excluded from the result. However, FPI indexes of both buyers' and sellers' provinces are positively related to the economic value.

Generally, high-value transactions take place between counterparties residing in the same or neighbouring provinces, presenting a negative relation to the distances.

Wednesday is the only significant variable with the economic value and shares the same positive effect as the volume. Similarly, November is the only influencing month on the economic value, but with a negative effect.

Regarding macro categories, food basket and fruit and vegetables are negatively related to the economic value, however, the variable "legumes" shows a positive impact.

Table 1
Coefficients of Forward Stepwise MLR model on Spec.1.

	Coefficients	Std. Error	P Value	
(Intercept)	−1122,00	268,96	0,000	***
FPI buyers	11704,08	1222,97	0,000	***
Distance	1,65	0,32	0,000	***
Meat	59,85	147,63	0,685	
Friday	−242,47	116,82	0,038	*
Fruit and vegetables	1480,67	359,15	0,000	***
Food basket	554,72	163,50	0,000	***
Legumes	524548,00	135,56	0,000	***
Saturday	−879,93	569,55	0,123	
February	884,81	340,57	0,009	**
Baby food	406,83	167,24	0,015	*
FPI sellers	−3935,55	1174,95	0,001	***
December	627,16	144,35	0,000	***
July	458,14	192,06	0,017	*
Wedensday	382,85	137,15	0,005	**
COVID cases (buyers)	−129,45	65,74	0,049	*
Canned food	301,42	171,52	0,079	.
Dairy	284,99	165,61	0,086	.
September	−257,39	174,91	0,142	

(FPI buyers and FPI sellers: FPI of buyers' and sellers' provinces; COVID cases (buyers): COVID cases reported in buyers' provinces).

3.2. RF model

We implement the RF model on the same equations to make a regression analysis and compare the results with those obtained from the Stepwise MLR approach. We expect the two models can unfold some hidden relations between the independent variables and target variable in our dataset. Furthermore, we can evaluate the two models' fitness regarding our analysis on the transaction volume and economic value.

Like the SMLR approach, we try to find out the most influencing variables on the transaction volume first, as shown in Fig. 2a.

Food poverty, distances, and COVID impact are the influencing variables. The model shows that Tuesday and Wednesday have more impact than the other days, and so the month of July, November, and December. Among the macro categories, legumes, canned food, baby food, and food basket are influencing the transaction volume. The model explains around 40.7% of the total variance.

The results of fitting RF model on the economic value are shown in Fig. 2b, which achieves a better explanation of the total variance (83.6%). As anticipated, the transaction volume is highly influential on the economic value. Food poverty has an important impact, followed by the distances and COVID indexes at the provincial level. For the timing variables, December, February, and July as of the influencing months, while Wednesday followed by Monday and Tuesday, has a greater influence. Among the macro categories, legumes and baby food have a more outstanding impact on the transaction value than other categories.

With the comparison of the Stepwise and the RF methods, substantial differences emerge. Stepwise method excludes the COVID impact per sellers' provinces on both the transaction volume and the economic value, and the significant effect of the COVID impact per buyers' provinces reflects only on the volume. RF model indicates them as the most

Table 2
Coefficients of Forward Stepwise MLR model on Spec.2.

	Coefficients	Std. Error	P Value	
(Intercept)	−8587	2347,4	0,000	***
Volume	7,5	0,31	0,000	***
Food basket	−8204,2	1480,31	0,000	***
Fruit vegetables	−18406,79	3308,57	0,000	***
Distance	−14,16	2,97	0,000	***
Legumes	3636,75	1201,1	0,003	**
November	−7365,85	2502,67	0,003	**
FPI buyers	27310,2	11026,34	0,013	*
FPI sellers	25237,62	8659,74	0,004	**
Wedensday	2494	1165,37	0,033	*

(FPI buyers and FPI sellers: FPI of buyers' and sellers' provinces).

Table 3
R^2 and RMSE values for the models.

Specification	R^2 RF	RMSE RF	R^2 Stepwise	RMSE Stepwise
1.Volume	0.407	1089.399	0.2405	1222.31
2.Economic Value	0.836	6041.115	0.4473	11565.22

important independent variables to the transaction volume and economic value. On the contrary, fruit and vegetables is a macro category with an influencing effect with the Stepwise approach, but it is excluded by RF model.

As shown in Table 3, we compare the R^2 values of the RF model (variance explained) and the RMSE between the SMLR and RF models. RF model presents the better R-squared and RMSE values for both equations. Therefore, the RF model is more suitable to study the drivers of the transaction volume and economic value.

3.3. Grouping transactions: the clustering approach

To evaluate if aggregating units can improve the explanatory capability of the models, we carry out a clustering analysis by grouping those

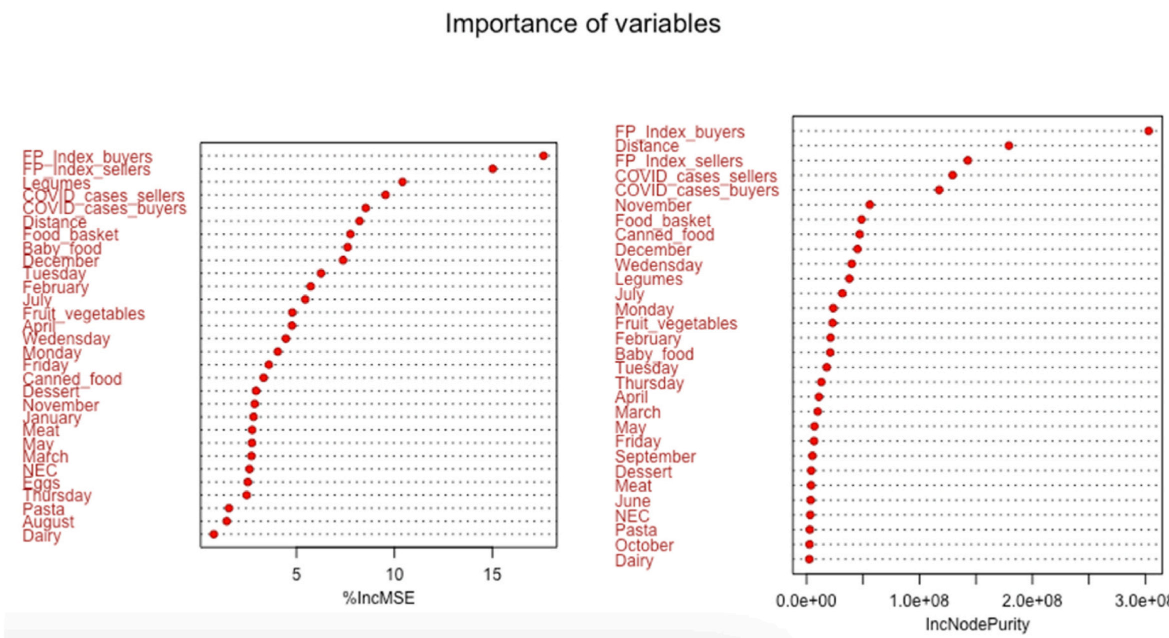

Fig. 2a. Importance of the independent variables that influence the transaction volume
(FP_Index_buyers: FPI of buyers' provinces; FP_Index_sellers: FPI of sellers' provinces; COVID_cases_buyers: COVID cases reported in buyers' provinces; COVID_cases_sellers: COVID cases reported in sellers' provinces; NEC: food category not classified).

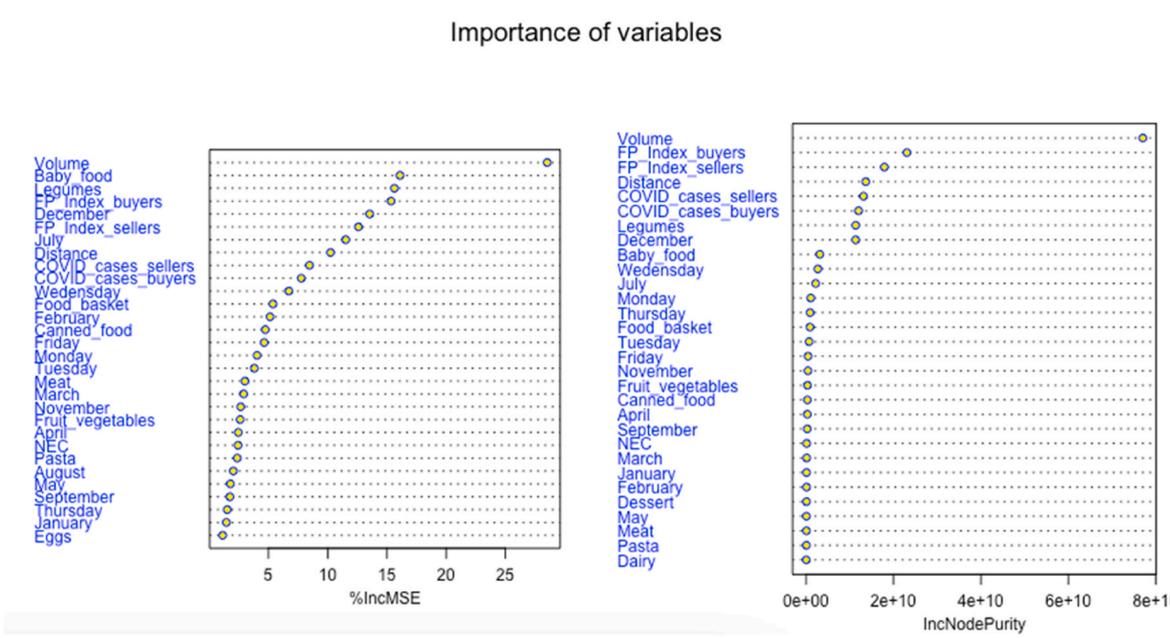

Fig. 2b. Importance of the independent variables that influence economic value of the transactions.
(FP_Index_buyers: FPI of buyers' provinces; FP_Index_sellers: FPI of sellers' provinces; COVID_cases_buyers: COVID cases reported in buyers' provinces; COVID_cases_sellers: COVID cases reported in sellers' provinces; NEC: food category not classified).

transactions with similar characteristics. A different model is implemented for each cluster afterwards with the RF algorithm and Stepwise method, with the aim of understanding if and to what extent different predictor variables act in different clusters. We also compare the results of the clustering approach with those obtained from the models in Section 2.

Our dataset has 866 observations and a mix of variable types including both numeric and categorical ones. To achieve a better clustering performance, hierarchical algorithm handles the scenario better than partitioning algorithm such as K-means [40]. Therefore, we decided to implement the most popular AGNES algorithm, which uses a bottom-up approach for clustering. The algorithm begins by considering each dataset point as a cluster, then it agglomerates the most similar data points with the criteria of minimum distance, maximum distance, average distance, and center distance into a single cluster. A dendrogram with clusters obtained by implementing AGNES algorithm to our dataset is shown in Fig. 3. To maintain a decent quantity of observations in each cluster, we set the number of clusters as 3. Cluster 1 had 367 observations, followed by smallest Cluster 2 (117 observations), and the last cluster 3 had 382 observations. We calculated the mean values of all variables per each cluster to see if there are outstanding features.

In the first cluster, most commercial transactions are about dairy, meat, and frozen food. Transaction of fruit and vegetables are the least. It excluded the transactions registered on Sunday.

The second cluster has the least transactions and is the most compacted in the dendrogram, however, it has the highest mean economic value, which is 10 times of cluster 1 and 20 times of cluster 3. Food poverty issue in this cluster is more obvious than in the other clusters. Interestingly, this is the only cluster with the FPI index of the buyers' provinces slightly higher than the index of the sellers. Most transactions are relevant to legumes and food basket, while no transaction is about frozen food. There is no transaction registered on Sunday or in January in this cluster.

The third cluster is composed of the most observations but with the shortest mean distance. The COVID impact on this cluster is the most profound. The most frequently traded macro categories are pasta, legumes, baby food, canned food, and NEC. Interestingly, categories like meat, frozen food, fruit, and vegetables are not grouped in this cluster. 54% of the transactions happened on Monday, and no transactions were on Saturday. Lastly, this cluster contains transactions mostly in December (97%), meanwhile no transactions were from February, March, July, August, or November.

3.4. Model estimation within clusters

After the clusters are constructed, we apply SMLR to the 3 clusters. As the previous section, the transaction volume, and the economic value as the two dependent variables in two different specifications.

We've got a few interesting results. Starting from the independent variables over the transaction volume, a positive relation stands between the distances and the transaction volume in cluster 1, which presents the smallest adjusted R^2 value ($R^2 = 0.2623$). Interestingly, the FPI index of the buyers' provinces is positively related to the volume, but there is no statistical significance of the sellers. Among the macro categories, baby food and food basket share positive relations with the volume, however, canned food shows a negative relation with the volume. Friday and July indicate a negative and a positive relation with the target variable respectively.

Interestingly, in the second cluster, the provincial COVID index of the counterparties shows opposite impact on the transaction volume. Lower is COVID's impact on the buyers' provinces, higher is the transaction volume, whereas higher transaction volume presents in the sellers' provinces with more COVID cases. Canned food, legumes, food basket, and fruit and vegetables are the macro categories with statistical significance; furthermore, all are linked to the transaction volume positively. In a year, December and February are positively relevant to the volume. In a week, Friday, Saturday, and Tuesday are negatively influencing the volume.

In the last cluster, COVID indexes and the distances are statistically significant with a positive influence, but the FPI indexes of the counterparties' provinces show different relations. The FPI index of the buyers' provinces has a positive relation with the volume, however, one of the sellers' provinces is negatively related to the volume. Legumes, dairy, dessert, baby food, canned food, and NEC of the macro category are all relevant to the transaction volume, however, only Legumes shows a positive effect. In this cluster, only Wednesday has a positive relation with the volume. January, April, September, and December all present a negative impact on the volume.

The average adjusted R^2 value of the three clusters is 0.3345 with an average RMSE value of 1013.5801, which is higher than the adjusted R^2 value of the Stepwise model without clustering. Compared with the RF model implemented without clustering, we observe a very small difference between the two R^2 values and RMSE values.

Regarding the drivers of economic value, the volume is always a positively influencing variable among all 3 clusters. In cluster 1, the FPI index of the sellers' provinces shows a positive effect. The statistically significant macro-category variables are baby food, canned food, and dessert with a positive relation, and food basket, and fruit and vegetables with a negative effect. July and September are positively related to the transaction value.

We see very few results in cluster 2. Legumes, meat, and canned food influence the economic value, but only canned food shows a negative relation. Timewise, December and September positively influence the economic value of the transactions, but November presents the opposite influence.

We have an interesting discovery in the third cluster, where the FPI index of the sellers' provinces has a positive impact on the economic value, but the FPI index of the buyers' provinces shows a negative

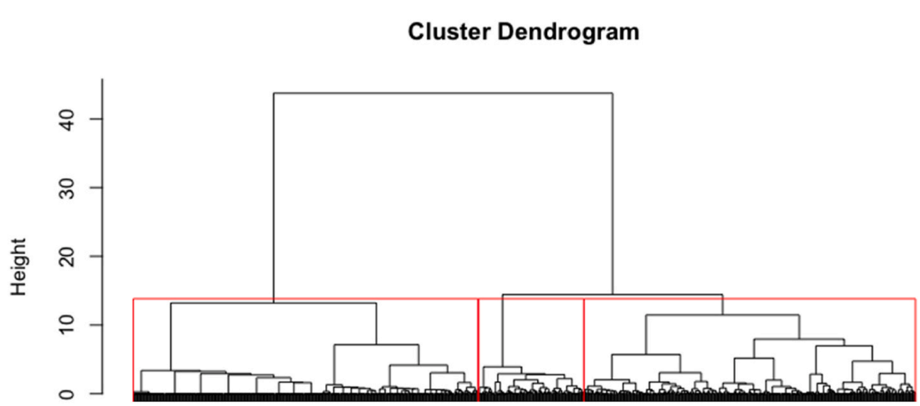

Fig. 3. Dendrogram of AGNES clustering.

impact. Also, the COVID index of the buyers' provinces shows a negative relation with the economic value, but nothing present for the COVID index of the sellers' provinces. Baby food and canned food are both positively related to the value, so is April the only month in a year that influences the target variable in the cluster.

The Stepwise method after clustering fitted better to the economic-value specification with an average adjusted R-squared value ($R^2 = 0.6747$) and average RMSE value (RMSE = 8009.6184). However, the RF model on the economic value without clustering still presents a better performance. Hence, clustering results in an improvement of the explanatory power in the models with the Stepwise method, but the RF model still fits better to analyse the drivers of the economic value.

We implement the RF model to the three clusters to analyse the potential improvements of the explanatory capability. We still set the transaction volume and the economic value as the two dependent variables in the specifications.

As shown in Fig. 4, FPIs and COVID indexes of the buyers' and sellers' provinces, and the distances are the major influencing factors over the transaction volume. Differences present among the three clusters. Take the macro categories as an example, legumes and food basket present a positive influence on the volume in all clusters, followed by pasta which positively influences the volume in Cluster 1 and 3. Canned food has a negative relation with the volume in Cluster 2, however, in Cluster 3, it has a positive effect. Baby food presents a positive effect only in cluster 1. We had different results among the three clusters regarding days in a week and months. In cluster 1, Thursday and Friday share a positive effect on the volume; July relates to the increase in volume, but Oct has a negative relevance. Monday and Tuesday have a positive relation with the volume in cluster 2; the same evidence was found for December and February, while July and September present a negative relation. In cluster 3, in a week, Wednesday shows a negative impact. April is the only month in a year influencing the volume negatively.

In comparison to the Stepwise method, the RF model with clustering seems to have a negative impact on the independent variables' power. A lower average R-squared value of the three clusters ($R^2 = 0.3173$) is registered for Spec.1 with clustering than the one without clustering.

Then we implement the RF model to the second specification with the economic value as the dependent variable, and we get the result as shown in Fig. 5. The importance of the volume over the economic value in all clusters shows the consistent pattern that we have seen from the previous implementations. The COVID and FPI indexes of the counterparties' provinces present positive relations with the economic values among all clusters, except in Cluster 3, the FPI of the buyers' provinces loses its significance. The particularity of the macro categories and time-featured variables exist again among the three clusters. In all clusters, legumes and pasta are statistically significant. Legume has always with a positive effect on the economic value, meanwhile, in cluster 1, pasta indicates a negative impact. Canned food influences the value negatively in cluster 1, but positively in cluster 3. Cluster 3 has much more influencing macro categories than the other two, for example, food basket, dessert, dairy, and baby food, which all have a positive relation. Wednesday, Thursday, and Friday have a positive effect on the economic value in cluster 1, and so does July. In cluster 2, Monday and Wednesday influence the value positively; November and December do as well, but June shows a negative impact. In cluster 3, Friday has a negative relation, while Tuesday is positively related to the economic value. In a year, December and April show a positive influence.

The average percentage variance explained (69.03%) is lower than the model without clustering (Table 4). Hence, the R-squared value is reduced for the RF model with clustering, no matter whether the dependent variable is the transaction volume or the economic value. Interestingly, when the volume is considered as the target variable, the explanatory capability of the variables performs better with the SMLR model than the RF model after we do the clustering.

In short, the clustering can improve the SMLR model, but not the RF model. When the transaction volume is the responsible variable, the performance of the RF model without clustering and the SMLR model with clustering is quite close. RF model without clustering results in a higher R^2 value but a slightly less-satisfied RMSE value in comparison to the improved Stepwise model after clustering. To further validate, we calculated the MSE values of both implementations (MSE = 557.5158 of the RF model and MSE = 635.7119 of the SMLR model) and we consider the RF model without clustering is still a better model to analyse the driven factors behind the transaction volume. For the economic value, the validating values gave us the same result as the RF model without clustering fitting better.

4. Conclusion

4.1. A methodological analysis: the fitted model and the obtained results

Firstly, we analysed two different models, Forward SMLR and RF to explain the main factors influencing the volume and the economic value of transactions recorded on the Regusto platform. The validation of the two models implemented on different targeted variables (volume and economic value) as well as on different approaches (before and after hierarchical clustering), revealed that the RF model achieved better explanatory and classification accuracy for our analysis. Contrastingly, the Stepwise algorithm not only obtained lower validation values but also excluded some independent variables that proved to be statistically significant in RF models. Although the hierarchical clustering approach did not improve our RF model, it is important to note that the result could be affected by the limited size of our dataset.

During the observation period, there were fewer transactions made for eggs, fruit and vegetables than for other food categories such as legumes and meat. Moreover, most transactions were made on week days and December witnessed the highest transaction volume, followed by the month of July, while transaction volumes hit their lowest level in August.

Table 5 shows a summary of the potential influencing factors indicated by the (coefficient) results of our models. The transaction volume is closely linked to the economic value as anticipated at the beginning of our analysis. Interestingly, food poverty and COVID effects show more positive correlations with economic value, however, this is not necessarily true for transaction volume. Food poverty levels in the sellers' regions could have a negative effect and the impact of the COVID crisis in the buyers' regions may have had similar consequences. Wednesday is the busiest transaction weekday, while July and December are the busiest transaction months, which all show positive relations between transaction volume and value. Among the 12 macro food categories, legumes and baby food were positively associated with volume and economic value. Furthermore, food basket and canned food also had a positive effect on volume.

4.2. Conclusion and managerial implication

The Regusto blockchain-empowered platform facilitates the management of surplus food but also increases food access in areas most at risk of food insecurity by searching, requesting, collecting, or purchasing available surplus food on the platform. Moreover, the digital platform excelled during the COVID-19 crisis. Both the donors/sellers and the beneficiaries/buyers benefited from this new distribution channel which can deliver a seamless customer experience and provide clear and transparent product information. This is further proven by our dataset, which maps out how surplus food traveled across Italy. Not only long distances between big cities with more inhabitants and agricultural provinces but also many short distances (36 Km as the shortest mean distance in a cluster and around 80 Km as the average distance of the overall sample).

The overall volume of food items transacted on the platform reached almost 350 thousand Kg with an impressive economic value of 1,84

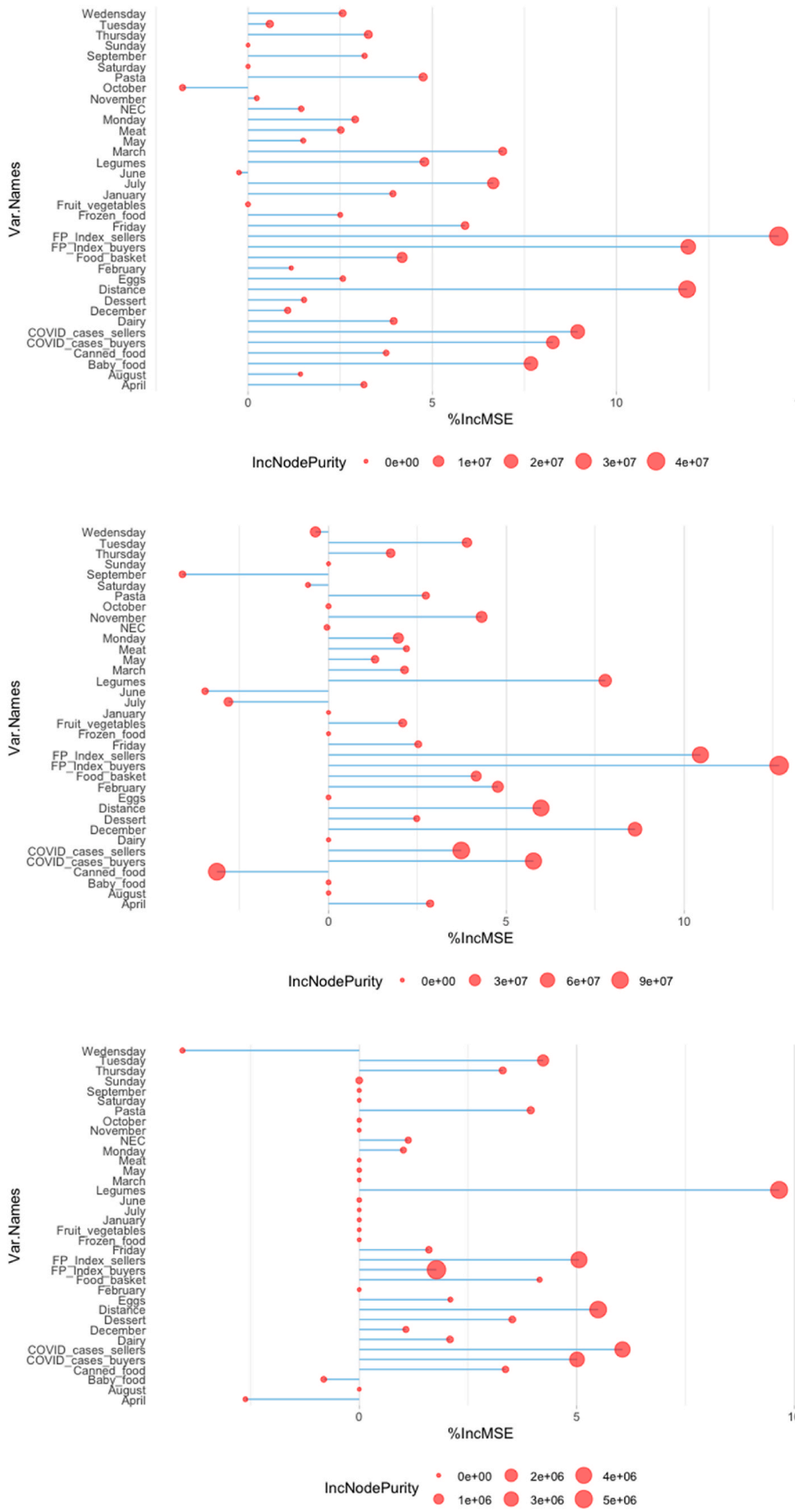

Fig. 4. Importance of independent variables that influence volume in 3 clusters
(FP_Index_buyers: FPI of buyers' provinces; FP_Index_sellers: FPI of sellers' provinces; COVID_cases_buyers: COVID cases reported in buyers' provinces; COVID_cases_sellers: COVID cases reported in sellers' provinces; NEC: food category not classified).

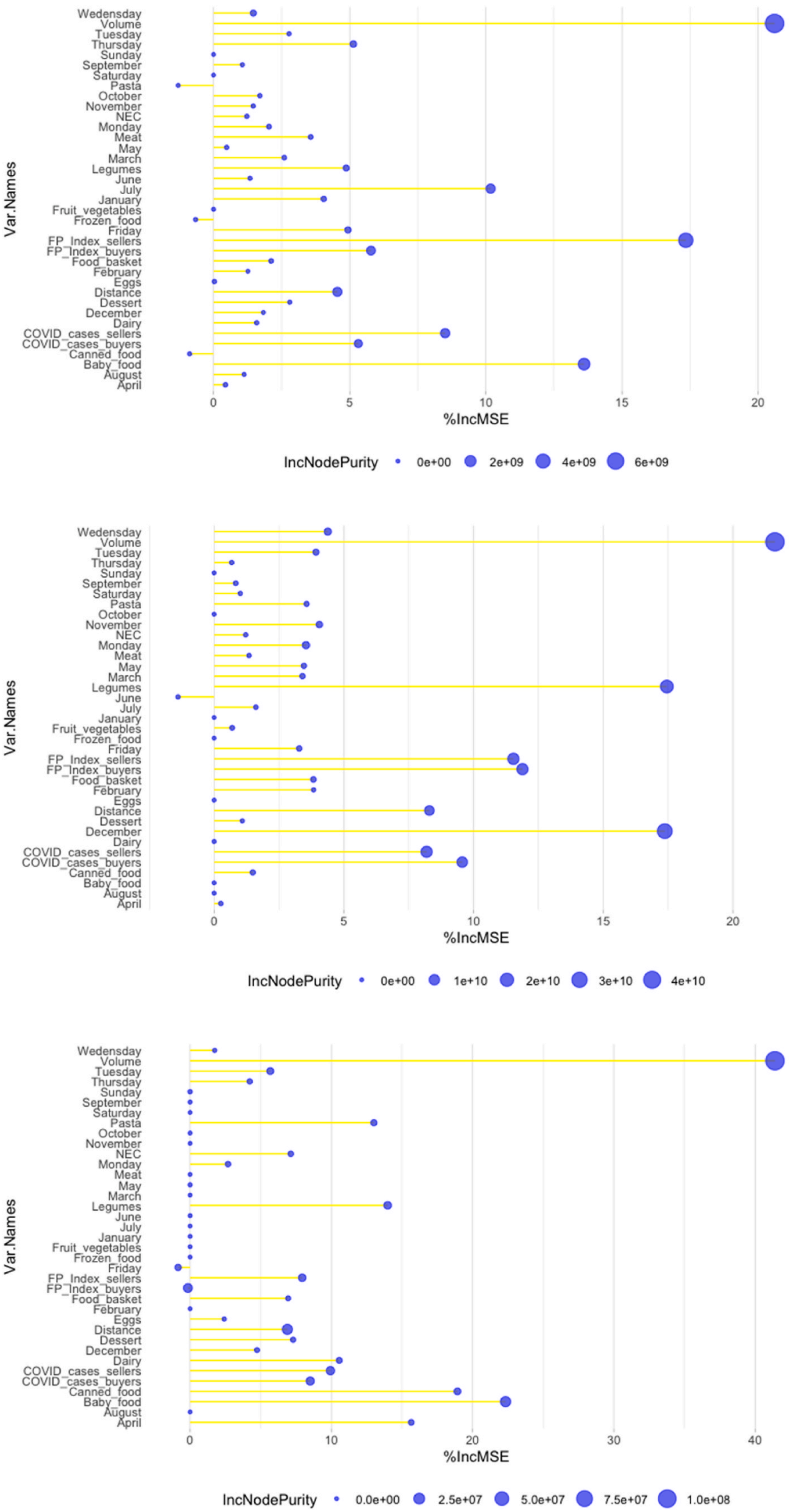

Fig. 5. Importance of independent variables that influence economic value of the transactions in 3 clusters
(FP_Index_buyers: FPI of buyers' provinces; FP_Index_sellers: FPI of sellers' provinces; COVID_cases_buyers: COVID cases reported in buyers' provinces; COVID_cases_sellers: COVID cases reported in sellers' provinces; NEC: food category not classified).

Table 4
R^2 and RMSE values for the models before and after clustering.

Specification	R^2 RF	RMSE RF	R^2 Stepwise	RMSE Stepwise
No clustering				
1. Volume	0.407	1089.399	0.2405	1222.31
2. Economic Value	0.836	6041.115	0.4473	11565.22
Clustering				
1. Volume	0.3173	1235.275	0.3345	1013.5801
2. Economic Value	0.6903	6596.4883	0.6747	8009.6184

million euros. It is not surprising that the Christmas period created greater volume and higher economic value, which is consistent with our model analysis. In our model, July showed a powerful positive effect on volume and value, while it is also the second highest month in a year in terms of transaction volume. However, few transactions were observed in the following month of August, which may be due to the traditional summer vacation period around mid-August in Italy. Therefore, policymakers and other players should plan more operations in July and December. This is also the case for Wednesdays because Wednesday is a key day for Regusto transactions. The vacation effect may also be extended to include Saturdays and Sundays as fewer transactions are made over the weekends. Since the Regusto platform is mainly used by businesses and NPOs, there are insufficient observations to support our analysis.

The existing food demand-and-supply network composed of NPOs, and various donors and suppliers has always had issues regarding poor transparency on product details, food quality and food safety. Blockchain technology provides tamper-proof product information which enables food integrity and traceability, which may greatly benefit the management of perishable and information-sensitive food products [37]. The Regusto platform facilitates the transaction of fruit and vegetables, eggs, dairy, meat, and baby food, which amounts to over 35% of its total transaction records. Transactions of meat products were frequently made (12.82% of the total transaction volume) – another proven contribution of blockchain technology to boost the redistribution of perishable and fresh food products. Baby foods may have also had similar promising marketing effects as a positive correlation can be seen *between* transaction volume and economic value in our model and legumes, food baskets and canned foods show statistical relationships in our analysis as well, which is important for Regusto's management and other players in the food supply chain. More industrial players who redistribute surplus food belonging to the aforementioned food categories should be involved and a new marketing channel should be developed. The findings are meaningful and motivating for policymakers and stakeholders in the food supply chain in terms of economic and social values. The main contribution of blockchain technology to Regusto's platform stands with improved efficiency. The key to the success of Regusto's platform is the presence of buyer and seller users on the platform and their activities to create transactions based on true supply-and-demand relationships - a new "eco-system" with a social character. In this case, policymakers and shareholders could take initiatives to lower the entry barrier due to costs and information gap, so that more players in the food value chain such as farms, small businesses and NPOs can participate. Regulations about food donations could take references to the transparent data captured by the surplus food transactions so that the donation activities can be encouraged without the compensation of food safety and security, especially the perishable and sensitive goods which are essential to achieving food security of vulnerable communities in our society. Shareholders and organizations shall take a step forward to embrace the benefits of digitalization, starting from system integration and internal training of the operational teams who will benefit from the increased working efficiency immediately.

Table 5
Summary of influencing factors over transaction volume and economic value with SMLR and RF models.

Influencing Factors	Stepwise	RF	Stepwise w. clustering	RF w. clustering
Transaction volume (P. = Positively, N. = Negatively)				
The distances	P.related	P.related	P.related	P.related
Food poverty	P.related with the buyers' provinces; N.related with the sellers' provinces	P.related	P.related with the buyers' provinces; N.related with the sellers' provinces	P.related
COVID impact	N.related with the buyers' provinces	P.related	P.related with sellers' provinces; N.related with buyers';	P.related
Weed days	P.related with Wed; N.related with Fri	Tue, Wed	P.related with Wed; N.related with Fri, Sat, Tue	P.related with Thur, Fri, Mon, Tue; N.related with Wed
Months	P.related with Feb, Dec, Jul	Jul, Nov, Dec	P.related Jul, Feb, Dec; N.related with Jan, Apr, Sept, Dec	P.related with Jul, Feb, Nov, Dec; N.related with Oct, Jul, Sept, Apr
Macro categories	P.related with fruit and vegetables, food basket, legumes, baby food, canned food, and dairy	Legumes, canned food, baby food, food basket	P.related with baby food, food basket, canned food, legumes, fruit and vegetables; N.related with canned food, dairy, dessert, baby food, canned food, NEC	P.related with baby food, food basket, legumes, pasta, canned food; N.related with canned food
Transaction economic value (P. = Positively, N. = Negatively)				
Volume	P.related	P.related	P.related	P.related
The distances	N.related	P.related	Null	P.related
Food poverty	P.related	P.related	P.related with FPI of the sellers' provinces; N.related with FPI of the buyers' provinces	P.related
COVID impact	Null	P.related	N.related with COVID index of the buyers' provinces in cluster 3	P.related
Weed days	P.related with Wed	Wed, Mon, Tue	Null	P.related with Wed; N.related with Fri
Months	N.related with Nov	Dec, Feb, Jul	P.related with Jul, Sept, Apr; N.related with Nov	P.related with Apr, Jul, Nov, Dec; N. related with Jun
Macro categories	P.related with legumes; N.related with food basket,	Legumes, baby food	P.related with legume, meat, baby food, dessert, canned food;	P.related with baby food, legumes, pasta,

(*continued on next page*)

Table 5 (*continued*)

Influencing Factors	Stepwise	RF	Stepwise w. clustering	RF w. clustering
	fruit and vegetables		N.related with food basket, fruit and vegetables, canned food	dessert, dairy, canned food N.related with canned food

4.3. Limitation and future development

However, our analysis is based on a relatively small sample size which might affect the accuracy of our model. The transaction volume and the economic value recorded do not portray the actual supply and demand. NPOs such as food banks not only deal with food poverty but also with surplus food which is donated to households that cannot consume it all, as reported in a survey on German food banks [15]. Cases of oversupply and dissatisfaction with Regusto can be further explored, which may improve our understanding of the relationships between specific food surplus categories and transactions and more importantly stop surplus food from going to waste at the consumer level. Our results for the categories of surplus food traded on the Regusto platform are very promising for legumes, meat and baby food, but much less so for eggs, fruit and vegetables. In the study on food banks in Germany conducted by Simmet et al [15], fruit, vegetables, baked goods, dairy products and meat were the most donated surplus food products. Concordant results were obtained for meat transactions, while fruit and vegetables revealed strong divergences. Extended case studies shall be followed in other regions and countries with a comparative analysis to measure the performances with the consideration of regional differences in culture, tradition, and other factors. On the other hand, comparison studies on blockchain technology and other digital innovations in food waste prevention and surplus food redistribution can deepen the understanding of the best practices. It is also important to pay attention to the drivers or obstacles of blockchain technology acceptance by industrial players. Technological competencies, cost estimation on implementation and maintenance, and managerial concerns are all worth mentioning [26].

Finally, according to recent studies, surplus food redistribution could have an inverse impact on the dietary habits and health of the beneficiaries [38] due to unequal food distribution thus poverty and food insecurity. However, further research and studies on hunger, food insecurity and nutrition are urgently required. Another field under discussion is the environmental benefits which should be measured with the positive outcomes of food redistributed and the potentially negative impact of the transportation-related operations [39].

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CRediT authorship contribution statement

Mengting Yu: Methodology, Writing – original draft, Writing – review & editing, Conceptualization, Formal analysis, Visualization, Data curation, Software. **Ludovica Principato:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing. **Marco Formentini:** Conceptualization, Data curation, Methodology, Writing – original draft, Writing – review & editing, Formal analysis, Visualization, Software. **Giovanni Mattia:** Conceptualization, Supervision, Writing – review & editing, Project administration. **Clara Cicatiello:** Conceptualization, Supervision, Writing – review & editing, Project administration. **Leonardo Capoccia:** Conceptualization, Supervision, Writing – review & editing, Project administration. **Luca Secondi:** Conceptualization, Data curation, Methodology, Supervision, Writing – review & editing, Project administration.

Data availability

The data that has been used is confidential.

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Abbreviations used in the paper

FSCM: Food supply chain management
CE: Circular Economy
FW: Food Waste
FLW: Food Loss and Waste
FSC: Food supply chain
NPOs: non-profit organizations
SMLR: Stepwise multiple linear regression
RF: random forest
SFR: Surplus Food Redistribution
B2NPO: Business-to-non-profit-organisation
FPI: Food poverty index
AGNES: Agglomerative NESting