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Bitcoin and Main Altcoins: Causality and Trading Strategies

Bitcoin e Principais Altcoins: Causalidade e Estratégias de Negociação

Soraia Santos
Helder Sebastião
Nuno Silva

ABSTRACT
Using daily data from November 9, 2017 to December 31, 2022, this paper uses Granger causality in the mean and the distribution to investigate the transmission of information between return, volume, volatility, and illiquidity for Bitcoin and the nine most important altcoins in terms of market capitalization. Additionally, the forecastability of Bitcoin returns is examined using linear models with different predictor spaces estimated using LASSO and the performance of several trading strategies devised upon those forecasts is assessed. The causal relationships between returns, volumes and volatilities of Bitcoin and each altcoin are more evident in the left tail of the distribution, where Bitcoin acts mostly as a transmitter of information, and in the right tail for causality regarding illiquidity. In bullish markets, Bitcoin acts mostly as a receiver of information. The best Bitcoin trading strategy is based on the model which incorporates the information on all cryptocurrencies, exhibiting a cumulative return of 331% and an annualized Sharpe ratio of 94.59%, considering an enter/exit threshold of 0.25% and after 0.5% round-trip transaction costs. These results are statistically significant when compared with the buy-and-hold strategy, which renders a cumulative return of 121% and a Sharpe ratio of 64.74%. These results point out the importance of considering information from other cryptocurrencies to forecast and trade on Bitcoin.
Keywords: Cryptocurrencies, Granger causality, LASSO, trading strategies.

JEL Classification: G11; G15; G17

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1. **Introduction**

Since Bitcoin's inception in 2008, cryptocurrencies have achieved an important role as an alternative means of payment to traditional currencies, and, most notably, as a means for highly speculative investments.

According to the CMVM (Comissão do Mercado de Valores Mobiliários, i.e., Portuguese Securities Market Commission, 2022), crypto-assets are "*digital representations of assets based on blockchain technology, not issued by a central bank, credit institution or electronic money institution and that can be used as a form of payment in a community that accepts it or have other purposes such as the attribution of the right to use of certain goods and services or to a financial return*".

Cryptocurrencies are the subject of hot debates. On the one hand, they are perceived by many as a key point of an ongoing digital revolution, where transparency and decentralization are highlighted. On the other hand, many others point out the risks associated with its speculative nature and the independence of accredited and reliable institutions to guarantee transactions. Nevertheless, it is remarkable that, several years after the launch of Bitcoin, the cryptocurrency market continues to grow, and Bitcoin prevails as a leader in terms of acceptance and market capitalization (Sebastião et al., 2021)

Recent studies have addressed various topics inherent to cryptocurrencies with the aim of better understanding this market. With the emergence of more and more altcoins (alternative cryptocurrencies to Bitcoin) thriving, a relevant topic that still raises questions in the literature is the causal relationship between these cryptocurrencies and Bitcoin, the oldest cryptocurrency and the one with the largest market capitalisation. As such, the first objective of this study is to contribute to this theme, by analysing the transmission of information between Bitcoin and nine major competing cryptocurrencies (Ethereum, Binance Coin, Ripple, Cardano, Dogecoin, Tron, Ethereum Classic, Litecoin and Chainlink), regarding their return, transaction volume, volatility and illiquidity. This study is conducted using Granger causality tests not only in the mean but also in all distribution support.

Secondly, the goal is to define various trading strategies for Bitcoin by forecasting its profitability and then evaluating its performance. To forecast Bitcoin returns, we consider not only past information about Bitcoin but also lagged information about other cryptocurrencies. Thus, the second objective of this study is to analyse various trading strategies, as well as understand whether the predictive power improves when other cryptocurrencies are added to the model and its impact on the trading strategies' performance.

The originality of this study comes from its overall framework. Although several studies tackle some issues dealt with here, we provide a coherent framework that considers several variables of different cryptocurrencies, considers not only causality in the mean but also in the distribution, uses LASSO to select dynamically the information set, makes forecasts pooling the models and assess statistically and economically the quality of the trading strategies devised upon the forecasts.

This study is structured into 6 sections. Section 2 presents a literature review that encompasses several studies on the relationship between cryptocurrencies and conventional financial assets, the transmission of information between cryptocurrencies, and trading strategies. Section 3 presents the raw and transformed data and some descriptive analysis. Section 4 explains the methodologies used to study the information transmission between

Bitcoin and other cryptocurrencies and the approaches to forecast the Bitcoin returns and evaluate trading strategies for this cryptocurrency. Section 5 presents the main results, and the last section concludes the paper.

2. **Literature Review**

Cryptocurrencies have gained attention as both payment methods and investment assets, prompting extensive research on their market dynamics, price determinants, and interactions with traditional financial markets. Studies frequently explore Bitcoin's market efficiency, price drivers, trading volume effects, and its role within the broader financial ecosystem.

Research on Bitcoin's market efficiency shows mixed results. Early studies suggest inefficiency (Kristoufek, 2018; Jiang et al., 2018), but others observe a progression towards efficiency over time (Urquhart, 2016; Wei, 2018). Urquhart (2016) employs randomness tests to find Bitcoin's market-approaching efficiency in recent sub-periods. Wei (2018) expands on this by examining 456 cryptocurrencies and finds a strong relationship between market efficiency, liquidity, and volatility. Conversely, Nadarajah and Chu (2017) conclude Bitcoin is efficient using an alternative methodology.

Balcilar et al. (2017) apply causality-in-quantiles to assess trading volume's impact on Bitcoin's return and volatility, noting predictive power in normal market conditions. This method is advantageous for analysing series with non-Gaussian, asymmetric distributions. Bouri et al. (2019) extend this to seven cryptocurrencies and find volume Granger-causes volatility under low volatility conditions. Dastgir et al. (2019) identify a bidirectional relationship between Bitcoin returns and Google Trends data.

Incorporating cryptocurrencies into the financial market context, Panagiotidis et al. (2018) identify Bitcoin return predictors, including gold returns and internet search intensity. Similarly, Ciner et al. (2022) find significant determinants, including VIX (implied volatility of a hypothetical S&P 500 stock option with 30 days to expiration) and gold prices, during COVID-19. Studies on the interrelation between cryptocurrencies and conventional assets yield conflicting results, with some suggesting market isolation (Ji et al., 2018; Corbet et al., 2018) and others indicating causal connections (Corbet et al., 2020; Bouri et al., 2018). Bitcoin is noted for its safe-haven properties, particularly against equity indices (Shahzad et al., 2019; Corbet et al., 2020).

Research on cryptocurrency interdependence highlights Bitcoin's dominance in information transmission (Koutmos, 2018; Raza et al., 2022), but other studies argue Bitcoin primarily receives information from other cryptocurrencies (Bação et al., 2018; Shahzad et al., 2022). Additionally, studies explore safe-haven and hedge properties (Li et al., 2023; Qiao et al., 2020) and the relationship between cryptocurrencies and fiat currencies (Corelli, 2018; Mokni and Ajmi, 2021). Kim et al. (2021) conclude that there is a significant causal relationship in the tail quantile, which makes it hard for investors to hedge the risk in the cryptocurrency market.

Profitability and trading strategies in cryptocurrency markets are another focus. Manahov (2023) demonstrates consistent profitability despite transaction costs. Momentum effects are explored by Caporale and Plastun (2020) and Bellocca et al. (2022), showing profitable trading patterns. Machine learning models enhance trading profitability (Sebastião and Godinho, 2021; Liu et al., 2023). Other strategies include moving averages (Grobys et al., 2020) and LASSO-based approaches (Huang and Gao, 2022). These studies suggest that machine learning and systematic trading strategies can be effective, robust and profitable.

The mixed evidence on Bitcoin's role in information transmission calls for more robust methodologies to explore interdependencies, particularly using advanced quantile and frequency-based analyses between different time series. Additionally, as machine learning models demonstrate potential in trading strategies, further research should optimize algorithmic approaches to adapt to rapidly changing market conditions and assess their robustness across different market phases.

3. Data and Preliminary Analysis

This study uses daily data retrieved from the CoinMarketCap website (https://coinmarketcap.com/) on the 10 cryptocurrencies with the highest market capitalization on January 1, 2023; excluding stablecoins and cryptocurrencies launched after 2018. These cryptocurrencies, ranked by decreasing market capitalization, are Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE), Binance Coin (BNB), Ripple (XRP), Cardano (ADA), Litecoin (LTC), Tron (TRX), Chainlink (LINK), and Ethereum Classic (ETC). The main cryptocurrency under study is BTC and we will refer to other cryptocurrencies as altcoins. Table 1 presents a summary description of these cryptocurrencies on January 1, 2023.

Table 1 – Summary description of cryptocurrencies on January 1, 2023

Crypto	Inception date	Market capitalization USD	Maximum supply	Circulating supply	Price USD	Daily trading volume USD
BTC	Jan. 2009	320,025	21	19	16,625.08	9,244
ETH	Jul. 2015	146,966	n.a.	122	1,200.96	2,400
DOGE	Dec. 2013	132,670	n.a.	132,671	0.070	185
BNB	Jul. 2017	39,053	n.a.	160	244.14	279
XRP	Jun. 2012	17,054	100,000	50,344	0.339	291
ADA	Sep. 2017	8,621	45,000	34,519	0.250	113
LTC	Oct. 2011	5,095	84	726	70.82	344
TRX	Aug. 2017	5,041	n.a.	91,961	0.055	100
LINK	Jun. 2017	2,856	1,000	508	5.622	109
ETC	Jul. 2016	2,188	211	139	15.77	56

Notes: This table presents a summary description of the 10 cryptocurrencies used in this study on January 1, 2023, which are Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE), Binance Coin (BNB), Ripple (XRP), Cardano (ADA), Litecoin (LTC), Tron (TRX), Chainlink (LINK), and Ethereum Classic (ETC). The market capitalization, maximum supply, circulating supply, and daily trading volume are presented in millions.

The period under scrutiny is from November 9, 2017, to December 31, 2022 (1,879 daily observations). The raw data includes the closing price, reported at 00:00:00 UTC (Coordinated Universal Time) of the following day, the daily high and low prices, and the daily trading volume in USD. These data were used to compute, for each cryptocurrency , the daily series of logarithmic returns using the closing prices, the log-volumes, the volatility, proxied by the Parkinson range estimator (Parkinson, 1980), and illiquidity, proxied by the Amihud illiquidity ratio (Amihud, 2002).

The Parkinson daily volatility estimator is defined by:

$$\sigma_{i,t}^{p} = \sqrt{\frac{1}{4\ln(2)} ln\left(\frac{H_{i,t}}{L_{i,t}}\right)^2}, \tag{1}$$

where $H_{i,t}$ and $L_{i,t}$ are the high and low prices of cryptocurrency i at day t.

Amihud's illiquidity ratio measures the impact on price resulting from a trade of one monetary unit. The daily Amihud illiquidity ratio is defined by:

$$ILLIQ_{i,t} = \frac{|r_{i,t}|}{V_{i,t}}, \tag{2}$$

where $r_{i,t}$ and $V_{i,t}$ correspond to the daily return and trading volume, in USD, of cryptocurrency i at day t. The ratio $ILLIQ_{i,t}$ was then multiplied by 10^8 to have a scale similar to the other variables.

According to the ADF (Augmented Dickey Fuller) test with constant and trend and a number of lags chosen by the BIC (Bayesian Information Criterion), all series are stationary except the log-volumes for some cryptocurrencies. Hence, hereafter we used the first difference of the log-volumes, which are stationary according to the ADF test.

Table 2 shows some descriptive statistics of daily return, first difference of the log-volume, volatility, and illiquidity of the 10 cryptocurrencies. The mean daily returns are very low, with the BNB achieving the highest value of 0.3%. The returns of the cryptocurrencies present a high variability, which is visible by the range and standard deviation. LINK presents the lowest minimum return, -61.5%, while DOGE has the highest maximum return, 151.6%. The standard deviation ranges from 4.0% for BTC to 7.8% for DOGE. Half of the cryptocurrencies have negative skewness and all have excess kurtosis, especially DOGE, with a value of 83.82. Finally, the return series do not show significant first-order autocorrelations, except for ETH and LINK, for the significance levels of 10% and 1%, respectively.

The maximum daily mean first difference of the log-volume is 0.002 (reached by DOGE, BNB, TRX and LINK). The variability is quite high, especially for BNB, with a minimum and a maximum of -9.092 and 9.063, respectively, and a standard deviation of 0.401. However, DOGE shows a higher standard deviation than BNB. All cryptocurrencies present distributions for first difference of the log-volumes with positive skewness, having values ranging from 0.054 for BTC to 1.405 for DOGE, as well as excess kurtosis, with a major highlight of BNB, which presents a value of 277.9. All volume series present significant first-order autocorrelations at a significance level of 1%.

The volatility series proxied by the Parkinson estimator show mean values ranging from 0.003 (BTC) to 0.009 (DOGE and LINK). The maximum value, 1.418, is present in the

DOGE series. As for the standard deviation, DOGE has, once again, the highest value (0.046) and BTC the lowest value (0.006). All series are skewed to the right, with DOGE having the highest value (19.93) and LINK the lowest value (7.655). All series exhibit high excess kurtosis, with DOGE standing out (522.1), and significant first-order autocorrelations at the 1% level.

The illiquidity, proxied by the Amihud ratio, presents average values from 0.000 for BTC to 0.745 for BNB. This last cryptocurrency presents a huge variability of illiquidity, with a minimum very close to 0 and a maximum of 1,335, being much lower in the other cases. As for the standard deviation, BNB stands out again with the highest value (30.83) and BTC has the lowest, very close to zero. All illiquidity series exhibit positive skewness and excess kurtosis, with BNB showing the highest values, 43.30 and 1,873, respectively. There is a significant first-order autocorrelation at a significance of 1% for all series, except BNB.

As expected, BTC stands out as the less volatile cryptocurrency in terms of return, first difference of the log-volumes, volatility, and illiquidity.

Table 2 – Descriptive statistics of returns, volumes, volatility, and illiquidity

	BTC	ETH	DOGE	BNB	XRP	ADA	LTC	TRX	LINK	ETC
Return										
Mean	0.000	0.001	0.002	0.003	0.000	0.001	0.000	0.002	0.002	0.000
Minimum	-0.465	-0.551	-0.515	-0.543	-0.551	-0.504	-0.449	-0.523	-0.615	-0.506
Maximum	0.225	0.235	1.516	0.529	0.607	0.862	0.389	0.787	0.481	0.353
Std dev.	0.040	0.051	0.078	0.059	0.064	0.067	0.055	0.070	0.071	0.063
Skewness	-0.821	-0.908	4.730	0.376	0.828	1.944	-0.129	1.952	-0.078	-0.106
Exc. Kurtosis	11.96	9.561	83.82	14.80	16.40	24.34	8.556	26.01	7.036	7.774
	-0.031	-0.042*	0.017	-0.009	0.004	-0.020	-0.025	0.028	-0.060***	-0.020
Volume										
Mean	0.001	0.001	0.002	0.002	0.000	0.001	0.000	0.002	0.002	-0.000
Minimum	-2.034	-1.083	-1.252	-9.092	-1.963	-1.135	-0.864	-1.029	-4.511	-1.764
Maximum	1.862	1.073	3.981	9.063	2.322	1.801	1.595	2.247	4.438	1.677
Std dev.	0.234	0.235	0.423	0.401	0.355	0.369	0.245	0.282	0.395	0.294
Skewness	0.054	0.296	1.405	0.134	0.682	0.569	0.756	0.984	0.565	0.598
Exc. Kurtosis	6.350	1.636	7.924	277.9	3.480	1.237	3.450	6.108	19.41	3.678
	-0.215***	-0.151***	-0.121***	-0.337***	-0.120***	-0.132***	-0.181***	-0.158***	-0.180***	-0.116***
Volatility										
Mean	0.003	0.004	0.009	0.006	0.007	0.007	0.005	0.008	0.009	0.007
Minimum	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	0.144	0.192	1.418	0.240	0.316	0.613	0.282	0.571	0.308	0.374
Std dev.	0.006	0.009	0.046	0.016	0.021	0.023	0.012	0.027	0.018	0.018
Skewness	11.45	11.46	19.93	8.850	8.749	15.48	11.09	10.93	7.655	10.55
Exc. Kurtosis	214.9	191.8	522.1	98.75	96.37	338.8	183.8	160.4	86.60	164.2
	0.429***	0.378***	0.337***	0.495***	0.381***	0.426***	0.340***	0.472***	0.455***	0.337***

	BTC	ETH	DOGE	BNB	XRP	ADA	LTC	TRX	LINK	ETC
Illiquidity										
Mean	0.000	0.001	0.111	0.745	0.003	0.040	0.004	0.034	0.619	0.009
Minimum	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	0.002	0.009	6.213	1,335	0.046	2.470	0.040	6.940	19.58	0.141
Std dev.	0.000	0.001	0.332	30.83	0.005	0.124	0.005	0.290	1.809	0.013
Skewness	3.234	3.418	8.692	43.30	3.670	11.25	2.562	17.19	5.253	3.418
Exc. Kurtosis	12.66	13.75	114.0	1,873	17.13	170.5	7.766	339.8	34.89	17.03
	0.443***	0.448***	0.526***	-0.001	0.527***	0.523***	0.480***	0.536***	0.616***	0.450***

Notes: This table presents the descriptive statistics of daily return, volume (first difference of the logarithm of trading volume), volatility, measured by the Parkinson estimator, and illiquidity, measured by the Amihud illiquidity ratio. These statistics are shown for the 10 cryptocurrencies with the highest market capitalization on January 1, 2023; excluding stablecoins and cryptocurrencies launched after 2018. The cryptocurrencies, ranked by descending market capitalization, are Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE), Binance Coin (BNB), Ripple (XRP), Cardano (ADA), Litecoin (LTC), Tron (TRX), Chainlink (LINK), and Ethereum Classic (ETC). The last line for each variable respects the first-order autocorrelation, . Significance at the 10%, 5% and 1% levels are denoted by *, **, ***, respectively. All the series are non-normal at the significance of 1% according to the Jarque-Bera test.

Table 3 presents the correlations between BTC daily returns and one-lagged returns, first difference of the log-volume, volatility, and illiquidity of each cryptocurrency.

Table 3 – Correlations between daily return of BTC and lag return, volume, volatility, and illiquidity of each cryptocurrency

Cryptocurrencies	Returns	Volume	Volatility	Illiquidity
BTC	0.031	0.005	0.058**	0.024
ETH	-0.072***	0.002	0.051*	0.007
DOGE	0.008	0.022	0.028	0.031
BNB	-0.046**	-0.018	0.020	-0.008
XRP	-0.081***	-0.043*	0.031	0.028
ADA	-0.034	0.011	0.042*	0.046**
LTC	-0.063***	0.010	0.037	-0.022
TRX	-0.020	0.022	0.025	0.059**
LINK	-0.023	0.008	0.061***	-0.006
ETC	-0.071***	-0.009	0.050**	0.005

Notes: This table presents the correlations between daily Bitcoin returns and one-lagged return, first difference of the log-volume, volatility, and illiquidity of each of the 10 cryptocurrencies. Significance at the 10%, 5% and 1% levels are denoted by *, **, ***, respectively.

The results presented in Table 3 highlight that the returns of all cryptocurrencies, except DOGE, on day $t-1$ are negatively correlated with the BTC returns on day t. ETH, XRP, LTC and ETC are significant at the 1% level. The correlations are lower for the other three variables. The only correlation significant at the 1% level is the lagged volatility of LINK, although there are other four cryptocurrencies with volatilities significant at 5% and 10%. The lagged first difference of the log-volume seems to have no information about BTC returns, except for XRP. The lagged illiquidity of ADA and TRX is positively correlated with BTC returns at the 5% significance level, and only the lagged volume of XRP is correlated at the 10% significance level. In a nutshell, this is a clear indication that BTC information is not especially important to forecast its returns, but the inclusion of altcoins in the forecasting models may have significant incremental information.

4. Methodology

This study investigates the Granger causality in the mean and the distribution between BTC and each of the nine most important altcoins in terms of market capitalization. These tests are applied to returns, volume (first difference of the log-volume), volatility and illiquidity. Then, the information on these variables up to time $t-1$ are used to forecast the value or signal of the BTC return at time t. These signals are then used to devise several trading strategies.

4.1. Granger Causality in the Mean and in the Distribution

The traditional Granger causality test (Granger, 1969) aims to ascertain whether the lags of a potential predictor introduce a significant additional contribution to the prediction of another variable, assuming the linearity of the relationship between the variables. Hence, it tests causality in the mean. Variable X does not Granger causes the variable Y if it does not contribute to its prediction, that is, if:

$$H_0{:}f\left(\mathrm{y}_t \mid \mathcal{F}_{t-1}^{x\&\mathrm{y}}\right) = f\left(\mathrm{y}_t \mid \mathcal{F}_{t-1}^{\mathrm{y}}\right), \forall Z \epsilon \mathbb{R}, \tag{3}$$

where $f\,(y_t|\mathcal{F})$ denotes the conditional distribution of y_t, $\mathcal{F}$ the information available at time t – 1, such that $\mathcal{F}_{t-1}^{X\&Y}$ corresponds to the information set with the past values of X and Y and $\mathcal{F}_{t-1}^{Y}$ includes only the past values of y , up to time t – 1.

To apply this test, it is usual to use bivariate VAR (Vector Autoregressive) models containing only endogenous variables. A VAR model consists of a system of simultaneous equations where each equation presents the contribution of lagged values of the variable itself and other endogenous explanatory variables of the model to the value of the dependent variable, allowing to capture of the linear interdependence relations between the variables. For instance, the equation for variable y_t in a VAR(p) is as follows:

$$\mathrm{y}_t = a_0 + \sum_{l=1}^{p} \alpha_l \mathrm{y}_{t-l} + \sum_{l=1}^{p} \beta_l x_{t-l} + \varepsilon_t, \tag{4}$$

where a_0 is the constant term, p is the number of lags of stationary variables Y and X, α_l and β_l (l = 1,...,p) are the coefficients of the lagged values of Y and X, respectively, and ε_t is the error term.

Variable X does not Granger-causes Y if $H_0{:}\beta_1 = \ldots = \beta_p = 0$. This hypothesis is tested through an F-test, which compares the unrestricted model, including the past values of X and Y, and the restricted model, including only the past values of Y:

$$F = \frac{(SSE_r - SSE_u)\,/p}{SSE_u\,/\,(T - (2p+1))} \quad F_{p,T-(2p+1)}\, if\ H_0\ is\ true, \tag{5}$$

where SSE_r and SSE_u denote the sum of squared errors from the restricted and unrestricted models, respectively, p is the number of omitted variables in the restricted model and T – (2p + 1) is the number of degrees of freedom, with T corresponding to the number of observations.

The number of lags to include in the VAR was obtained through the multivariate version of the HQC criterion (Hannan-Quinn Criterion) given by $HQC = -2\ell(\hat{\theta}) + 2kloglog(T)$, where $\ell(\hat{\theta})$ is the maximum loglikelihood as a function of the vector of parameter estimates, $\hat{\theta}$ is the vector of estimated parameters, and k is the number of parameters.

The linear causality test causality has been extensively used in macroeconomic and financial applications. More recently, new methodologies have generalized the concept of Granger causality to quantiles and regions of the distribution. The causality test on tail events proposed by Hong et al. (2009) assumes that a tail event occurs when the value of a time series is lower than its VaR (Value-at-Risk) at a specific risk level α%. The $VaR_{\alpha\%}$ measures the largest possible loss within a confidence interval of α%. The test seeks to determine whether extreme events in a time series contribute to the prediction of extreme events in another time series. The methodology of Hong et al. (2009) has the limitation of being performed in a specific quantile. Candelon and Tokpavi (2016) propose a methodology with a higher testing power, which allows testing Granger causality for several quantiles simultaneously and hence has the flexibility to test specific regions of the distributions supports. Candelon and Tokpavi (2016) is a multivariate extension of Hong et al. (2009), using different VaR levels. For series Y and X:

$$\begin{aligned} Pr\left[Y_t < VaR_t^Y(\theta_Y^0) \mid \mathcal{F}_{t-1}^Y\right] &= \alpha, \\ Pr\left[X_t < VaR_t^X(\theta_X^0) \mid \mathcal{F}_{t-1}^X\right] &= \alpha. \end{aligned} \tag{6}$$

where $VaR_t^Y(\theta_Y^0)$ and $VaR_t^X(\theta_X^0)$ are the VaRs of Y and X, respectively, at time t, and θ_Y^0 and θ_X^0 are the true unknown finite-dimensional parameters related to the VaR models for Y and X, given the information set at time $t-1$.

Let $A = \{\alpha_1,\ldots,\alpha_{m+1}\}$ be a set of $m+1$ VaR levels, covering the distributions support of the variables Y and X, such that $0 < \ldots < \alpha_s \ldots < \alpha_{m+1} < 100\%$, therefore partitioning the support into m disjoint regions. For the series Y, the VaRs at time t are denoted by $VaR_{s,t}^Y(\theta_Y^0,\alpha_s)$, $s = 1,\ldots,m+1$, such that

$$VaR_{1,t}^Y(\theta_Y^0,\alpha_1) < \ldots < VaR_{m+1,t}^Y(\theta_Y^0,\alpha_{m+1}). \tag{7}$$

By convention, $VaR_{s,t}^Y(\theta_Y^0,\alpha_s) = -\infty$ for $\alpha_s = 0\%$ and $VaR_{s,t}^Y(\theta_Y^0\alpha_s) = +\infty$ for $\alpha_s = 100\%$.

The event variable, related to the m disjoint regions of the distribution support of Y, is defined by:

$$Z_{s,t}^Y(\theta_Y^0) = \begin{cases} 1, \text{ if } Y_t \geq VaR_{s,t}^Y(\theta_Y^0,\alpha_s) \text{ and } Y_t < VaR_{s+1,t}^Y(\theta_Y^0,\alpha_{s+1}) \\ 0, \text{ otherwise} \end{cases} \tag{8}$$

Note that the event variable for the series X is defined analogously.

Let $H_t^Y(\theta_Y^0)$ and $H_t^X(\theta_X^0)$ be the vectors of dimension $(m, 1)$ that contains the components of the m event variables for series X and Y defined respectively by:

$$\begin{aligned} H_t^Y(\theta_Y^0) &= \left[Z_{1,t}^Y(\theta_Y^0), Z_{2,t}^Y(\theta_Y^0), \ldots, Z_{m,t}^Y(\theta_Y^0)\right]', \\ H_t^X(\theta_X^0) &= \left[Z_{1,t}^X(\theta_X^0), Z_{2,t}^X(\theta_X^0), \ldots, Z_{m,t}^X(\theta_X^0)\right]'. \end{aligned} \tag{9}$$

Then X does not Granger-causes Y in distribution if the following null hypothesis is not rejected:

$$H_0{:}\,\mathbb{E}\big[H_t^Y(\theta_Y^0)\mid \mathcal{F}_{t-1}^{X\&Y}\big]=\mathbb{E}\big[H_t^Y(\theta_Y^0)\mid \mathcal{F}_{t-1}^{Y}\big]. \tag{10}$$

Therefore, Granger causality in distribution from X to Y corresponds to causality in mean for each $H_t^X(\theta_X^0)$ to $H_t^Y(\theta_Y^0)$.

The test can be applied to different regions of the distribution support, such as the centre, the left and right tails, by simply restricting the set $A=\{\alpha_1,\ldots,\alpha_{m+1}\}$ to the desired risk levels. This study considers the left tail by setting $A=\{1\%, 5\%, 10\%\}$, the right tail by setting $A=\{90\%, 95\%, 99\%\}$, and the centre of the distribution, by setting $A=\{20\%, 30\%, 40\%, 50\%, 60\%, 70\%, 80\%\}$.

Let $\hat{H}_t^Y=H_t^Y(\hat{\theta}_Y)$ and $\hat{H}_t^X=H_t^X(\hat{\theta}_X)$ be the estimated counterparts of the multivariate process of the event variables $H_t^Y(\theta_Y^0)$ and $H_t^X(\theta_X^0)$, respectively, with $\hat{\theta}_Y$ and $\hat{\theta}_X$ being the $\sqrt{T}$-consistent estimators of the unknown parameter vectors θ_Y^0 and θ_X^0. $\hat{\Lambda}(j)$ is the sample cross-covariance matrix between $\hat{H}_t^Y$ and $\hat{H}_t^X$ such that:

$$\hat{\Lambda}(j)=\begin{cases} T^{-1}\displaystyle\sum_{t=1+j}^{T}(\hat{H}_t^Y-\hat{\Pi}_Y)(\hat{H}_{t-j}^X-\hat{\Pi}_X)', 0\le j\le T-1,\\ T^{-1}\displaystyle\sum_{t=1-j}^{T}(\hat{H}_{t+j}^Y-\hat{\Pi}_Y)(\hat{H}_t^X-\hat{\Pi}_X)', \qquad \textit{otherwise.}\end{cases} \tag{11}$$

The vectors $\hat{\Pi}_Y$ and $\hat{\Pi}_X$ of dimension m are the sample means of $\hat{H}_t^Y$ and $\hat{H}_t^X$, respectively. Like in Hong et al. (2009), $\hat{\Pi}_Y=\mathbb{E}\big[H_t^Y(\theta_Y^0)\big]$ and $\hat{\Pi}_X=\mathbb{E}\big[H_t^X(\theta_X^0)\big]$, without the asymptotic distribution of the test statistic being affected.

The sample cross-correlation matrix, $\hat{R}(j)$, is given by:

$$\hat{R}(j)=D(\hat{\Sigma}_Y)^{-1/2}\hat{\Lambda}(j)D(\hat{\Sigma}_X)^{-1/2}, \tag{12}$$

in which $D(.)$ represents the diagonal form of a matrix and $\hat{\Sigma}_Y$ and $\hat{\Sigma}_X$, which are the sample covariance matrices of $\hat{H}_t^Y$ and $\hat{H}_t^X$, respectively.

Considering further a kernel function $k(.)$, a truncation parameter M and a function $\hat{Q}(j)$, defined by:

$$\hat{Q}(j)=T\big[vec(\hat{R}(j))'\big](\hat{\Gamma}_Y^{-1}\otimes\hat{\Gamma}_X^{-1})\,vec(\hat{R}(j)), \tag{13}$$

where the operator *vec* vectorises the matrix, $\otimes$ corresponds to the Kronecker product, and $\hat{\Gamma}_Y$ and $\hat{\Gamma}_X$ are the sample correlation matrices of $\hat{H}_t^Y$ and $\hat{H}_t^X$, respectively.

The test statistic associated with the null hypothesis of non-causality can be represented by a weighted quadratic form that considers the dependence between the current value of $\hat{H}_t^Y$ and the lagged values of $\hat{H}_t^X$, that is, by:

$$\hat{\mathfrak{I}} = \sum_{j=1}^{T-1} k^2\left(\frac{j}{M}\right)\hat{Q}(j). \tag{14}$$

The test statistic of Candelon and Tokpavi (2016) is a centred and scaled version of the quadratic form present in the previous equation:

$$V_{X\rightarrow Y} = \frac{\hat{\mathfrak{I}} - \mathfrak{m}^2 C_T(M)}{\left(m^2 D_T(M)\right)^{1/2}}, \tag{15}$$

where $C_T(M)$ and $D_T(M)$ are the location and scale parameters, corresponding respectively to:

$$C_T(M) = \sum_{j=1}^{T-1}(1 - j/T)\,k^2(j/M), \tag{16}$$

$$D_T(M) = 2\sum_{j=1}^{T-1}(1 - j/T)(1 - (j+1)/T)\,k^4(j/M). \tag{17}$$

Under the null hypothesis of no causality in distribution, $V_{X\rightarrow Y} \sim N(0,1)$.

As discussed by Hong et al. (2009), the choice of kernel, except for the case of the uniform kernel that does not eliminate higher-order lags, is not relevant as it leads to comparable test powers. In this study, we will resort to the Bartlett kernel.

Candelon and Tokpavi (2016) consider three values for the truncation parameter M, namely $ln(T)$, $1.5T^{0.3}$, and $2T^{0.3}$. We have tested these values with similar results. Hence, results are presented for $1.5T^{0.3}$, which, given the sample size, is 14.

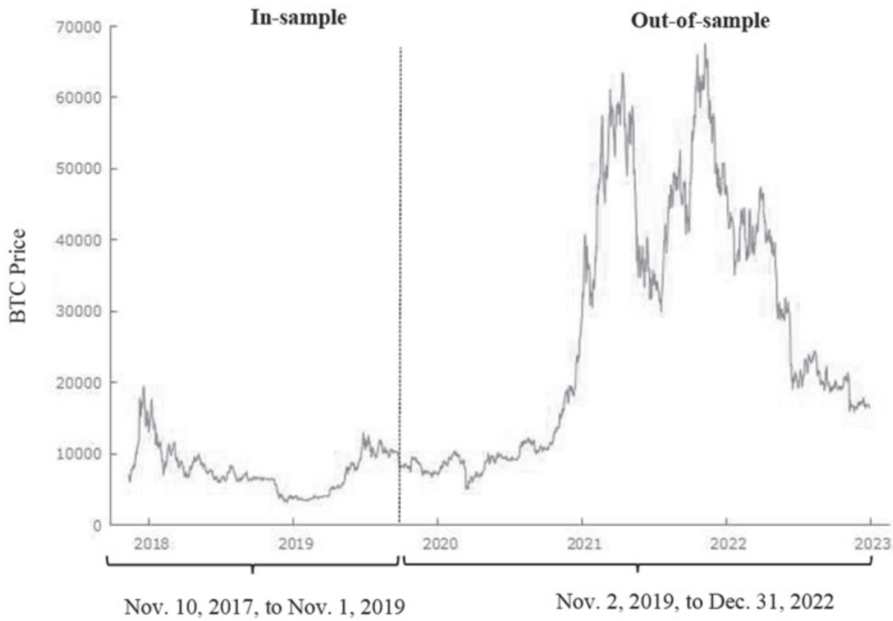
4.2. Forecasting and Trading on Bitcoin

This subsection explains the procedures used to forecast BTC returns and to devise trading strategies based on those forecasts.

The total period was partitioned into in-sample and out-of-sample. The in-sample is from November 10, 2017, to November 1, 2019, and the out-of-sample period is from November 2, 2019, to December 31, 2022, so that T_1 = 722 and T_2 = 1,156 (see Figure 1). A rolling window with a fixed length of 714 observations, was used to forecast BTC returns based on the lagged information on returns, volumes, volatility, and illiquidity series of BTC and the other nine altcoins. We consider 11 models with BTC returns as the dependent variable and different predictor spaces with lags of 1 to 7 to capture any day-of-the-week effect.

One model only considers BTC, nine models use BTC and an altcoin, and the last model uses all the information.

Figure 1 – Evolution of Bitcoin closing price and partition into in- and out-of-sample.



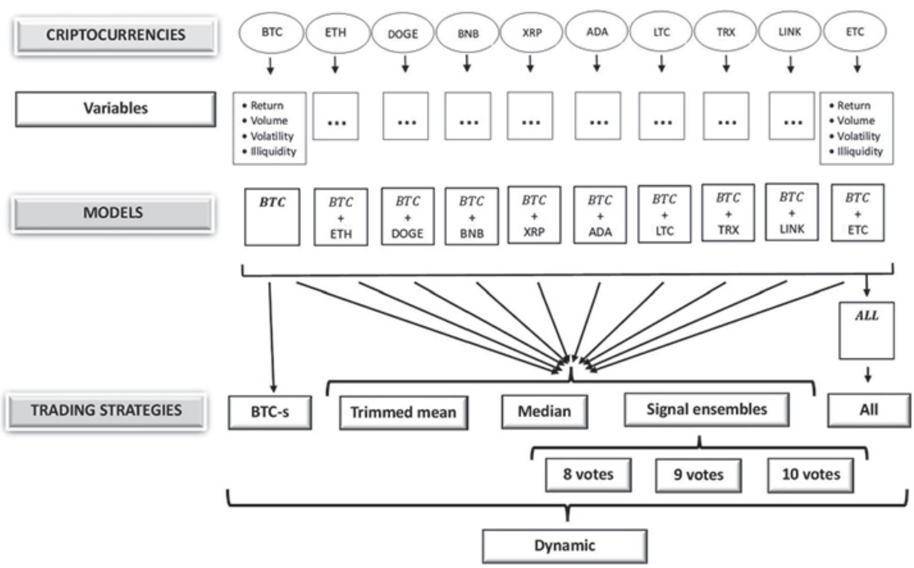
The forecasting models are then used to devise the following eight trading strategies:

- Strategy "BTC-s" considers the information of BTC only (7 x 4 = 28) explanatory variables.
- Strategies "Trimmed mean" and "Median" use the trimmed mean and median of the forecasts obtained from ten regressions, one for each cryptocurrency with 28 explanatory variables, respectively. The trimmed mean is the arithmetic average of the six forecasts, excluding the two lowest and two highest forecasts.
- The "Signal ensembles", consider the signals of the ten forecasts obtained from the model with BTC and from the nine models with the information of BTC and each cryptocurrency (in these models, there are 2 x 7 x 4 = 56 explanatory variables). The investor enters, stays in, stays out or exits the market if eight, nine and ten models agree on the signal of the forecasts (these strategies are called hereafter "8 votes", "9 votes" and "10 votes", respectively).
- Strategy "All" considers as the predictor space all the lagged information of the ten cryptocurrencies (in total 10 x 7 x 4 = 280 variables).

- Finally, the "Dynamic" strategy chooses the best one, step-by-step, among the previous seven strategies. For each day, the best strategy is the one that minimizes the MSE (mean squared error) of the previous seven days (in case of a tie, the strategy with the model with the highest cumulative return in the previous days is adopted).

Figure 2 illustrates the research framework for trading strategies, referring to the cryptocurrencies, variables, forecasting models, and trading strategies used.

Figure 2 – Research framework for trading strategies



The models were estimated using the LASSO (Least Absolute Shrinkage and Selection Operator) procedure proposed by Tibshirani (1996) to remove redundant variables and select the relevant regressors. The LASSO estimator is defined as:

$$\hat{\beta}_{LASSO} = \operatorname{argmin}\left\{ \sum_{t=8+k}^{t_1+k} \left(\mathrm{y}_t - \beta_0 - \sum_j \beta_j x_{tj} \right)^2 + \lambda \sum_j \beta_j^{\,2} \right\}, \lambda \geq 0, \tag{18}$$

where y_t and x_{tj} correspond to the observations of the dependent and the explanatory variables j at time t, respectively, out of a total of $T_1 - 7$ observations, where T_1 is the in-sample size, and the optimization problem is solved for $k = 0,\ldots,T_2 - 1$, where T_2 is the end of the out-of-sample. β_j is the regression coefficient corresponding to x_j and β_0 is the constant term of the model. Finally, λ is the regularisation parameter (penalty), which allows the elimination of redundant coefficients. The higher its value, the higher the penalty and the number of null coefficients.

The choice of the regularization parameter was carried out through a 10-fold cross-validation. Briefly, this method divides the period into ten disjoint subsets of approximately equal size and trains the model in nine subsets which are applied to the remaining subset. This procedure is replicated ten times. The cross-validation performance corresponds to the average of a performance measure across the ten subsets. In our case, the λ is the one that minimizes the MSE in the previous week, that is:

$$MSE = \frac{1}{T_1 - 7} \sum_{t=8+k}^{T_1+k} (y_t - \hat{y}_t)^2, \tag{19}$$

where y_t and $\hat{y}_t$ are the observed and estimated value of the dependent variable, respectively, and $k = 0,...,T_2 - 1$.

The trading strategies only consider positive or null positions in BTC, implying that short selling is precluded. Hence the investor is unable to capitalize on negative forecasts. The action taken by the investor depends on the forecasts of the trading strategies and a threshold. This threshold is set equal to the proportional transaction costs of 0.25% which is higher than the figures used in the literature for BTC (Alessandretti et al., 2018, Sebastião and Godinho, 2021). The procedure is the following. If the forecast at day t is higher than 0.25%, the investor enters or stays in the market at day $t + 1$ if at day t the position is null or positive, respectively. If the forecast at day t is lower than -0.25%, the investor exists or stays out of the market at day $t + 1$ if at day t the position is positive or null, respectively. The Signal ensembles add an additional step. For each model (BTC and BTC and each altcoin) the forecast is made, and the signal is recorded (1 if the forecast is higher than 0.25% and 0 if the forecast is lower than -0.25%). If the number of models with a given signal is equal to or higher than a given boundary the investor takes action. For instance, for the strategy "8 votes" the investor gets out or stays out of the market if the sum of ones is lower than 8 and enters or stays in the market otherwise.

The three best strategies according to the Sharpe ratio are compared with the passive Buy-and-hold (B&H) strategy and the BTC-s strategy. To compare the performance of all strategies, the strategies are analysed from $T_1 + 8$ to T_2, 1,149 observations (hence excluding the first 7 observations of the out-of-sample period, due to the dynamic strategy). Several performance metrics are computed with proportional trading costs and entry/exit barrier of 0.25%.

(1) The relative number of days in the market in which a long position is active.

(2) The win rate corresponds to the percentage of days in the market in which the strategy returns a positive return.

(3) The cumulative return after trading costs given by the exponential of the sum of the daily continuous returns of strategy over the entire evaluation, i.e., $\exp(\sum r_{j,t}) - 1$.

(4) The annualized mean return.

(5) The annualized standard deviation of returns.

(6) Assuming that the risk-free rate is zero, the annualized Sharpe ratio is the ratio between the return, $\hat{\mu}_j$, and the standard deviation, $\hat{\sigma}_j$:

$$SR_j = \sqrt{365}\frac{\hat{\mu}_j}{\hat{\sigma}_j}. \tag{20}$$

(7) The bootstrap p-values corresponding to the probabilities of the daily Sharpe ratio of the active strategy, considering all days in the sample, are higher than the daily Sharpe ratio of the B&H and BTC-s strategies.

(8) The annualized Sortino ratio which considers in the denominator the downside risk from a target value, which we assume is equal to zero:

$$STR_j = \sqrt{365}\frac{\hat{\mu}_j}{\sqrt{\frac{1}{T_2 - T_1 - 8}\sum_{t=T_1+8}^{T_2} \min\left[r_{j,t}, 0\right]^2}} \tag{21}$$

(9) The annualized certainty equivalent of a CRRA (Constant Relative Risk Aversion) utility function such that:

$$U(W_t) = \begin{cases} \frac{W_t^{1-\gamma}}{1-\gamma}, & if\ \gamma > 1 \\ \ln(W_t), & if\ \gamma = 1 \end{cases} \tag{22}$$

where W_t denotes investor wealth at t and γ is the risk aversion parameter is given by:

$$CE_j = \begin{cases} \left[\left(\frac{1}{T_2 - T_1 - 8}\sum_{t=T_1+8}^{T_2} \hat{W}_{j,t}^{1-\gamma}\right)^{\frac{365}{1-\gamma}} - 1\right] & if\ \gamma \neq 1 \\ 365\left[\frac{1}{T_2 - T_1 - 8}\sum_{t=T_1+8}^{T_2} \log \hat{W}_{j,t}\right] & if\ \gamma = 1 \end{cases}, \tag{23}$$

where $\hat{W}_t = e^{r_{j,t}}$ (we considered γ = 1, 3, 5).

(10) Lastly, the CVaR$_{\alpha\%}$ (Conditional Value-at-Risk at α%) measures the average loss conditional on a VaR exceeded at the $\alpha\%$ = 1%, 5%.

5. Results

5.1. Causality in the Mean and in the Distribution

Table 4 and Table 5 present the tests on Granger causality in the mean and in the distribution, respectively, between BTC and the altcoins. In discussing these results, we mainly focus on those that are significant at the 1% level.

Table 4 – Granger causality in the mean between Bitcoin and each altcoin

	Returns		Volume		Volatility		Illiquidity	
i	$F_{BTC\to i}$	$F_{i\to BTC}$	$F_{BTC\to i}$	$F_{i\to BTC}$	$F_{BTC\to i}$	$F_{i\to BTC}$	$F_{BTC\to i}$	$F_{i\to BTC}$
ETH	1.140	5.236**	2.699***	1.498	2.339*	3.052**	2.081**	1.602
DOGE	4.208***	0.745	2.883***	1.738*	1.168	1.791	1.559	1.494
BNB	2.137	1.591	5.229***	2.103**	3.020**	3.101***	0.222	3.893***
XRP	3.807*	6.138**	3.803***	1.489	0.683	1.709	3.520***	1.498
ADA	1.238	4.146**	5.270***	2.209**	2.065**	2.459**	2.556**	2.703***
LTC	0.405	3.732*	2.635**	0.665	8.030***	7.644***	0.706	2.704***
TRX	2.383*	0.037	3.629***	1.750*	2.805***	2.559**	1.524	3.337***
LINK	1.031	0.045	3.443***	2.482**	4.502***	4.403***	0.633	1.668
ETC	1.480	4.530**	1.906*	2.079**	2.344*	1.953*	1.739*	2.375**

Notes: $F_{BTC\to i}$ and $F_{i\to BTC}$ denote the statistics of the linear Granger causality test from BTC to altcoin i and from altcoin i to BTC, respectively. Significance at the 10%, 5% and 1% levels are denoted by *, **, ***, respectively.

Granger causality in the mean runs only from the returns of BTC to DOGE. In terms of the first difference of the log-volume, the causality runs from BTC to all altcoins, except LTC and ETC. At the 1% significance level, there is bidirectional causality between BTC and LTC and BTC and LINK. Additionally, at this significance level, there is causality from BTC to TRX and from BNB to BTC. The causality in illiquidity runs mainly from altcoins to BTC, namely from BNB, ADA, LTC and TRX. Only BTC Granger causes the XRP illiquidity at the 1% level.

Table 5 shows the Granger causality tests in distribution, applied to the left tail (bearish market), right tail (bull market) and the central region (calm market) between BTC and the nine altcoins for return, volume, volatility, and illiquidity.

Table 5 – Granger causality in the distribution between Bitcoin and each altcoin

	Left tail		Centre		Right tail	
	$V_{BTC\to i}$	$V_{i\to BTC}$	$V_{BTC\to i}$	$V_{i\to BTC}$	$V_{BTC\to i}$	$V_{i\to BTC}$
Return						
ETH	-0.031	0.497	0.622	0.130	0.226	-1.006
DOGE	0.260	0.406	-0.253	0.716	-0.494	0.948
BNB	3.163***	0.750	-0.987	3.243***	-1.333	-0.850
XRP	1.133	1.541	0.297	1.020	0.915	2.148**
ADA	0.229	-1.153	1.250	-0.217	-1.223	-0.934
LTC	2.316**	-0.673	0.116	1.038	0.813	-0.392

	Left tail		Centre		Right tail	
	$V_{BTC\rightarrow i}$	$V_{i\rightarrow BTC}$	$V_{BTC\rightarrow i}$	$V_{i\rightarrow BTC}$	$V_{BTC\rightarrow i}$	$V_{i\rightarrow BTC}$
Return						
TRX	1.927*	1.133	-0.994	2.959***	-0.309	1.470
LINK	0.872	-1.004	-1.098	2.204**	-0.879	-1.457
ETC	2.350**	-0.659	0.232	1.097	-0.119	-0.072
Volume						
ETH	4.234***	4.787***	-0.262	-0.215	-0.586	0.604
DOGE	1.898*	2.105**	3.038***	-0.936	0.547	0.199
BNB	2.708***	-0.106	-0.354	-0.655	1.485	0.408
XRP	5.521***	4.293***	-1.309	-1.576	0.088	-0.050
ADA	3.688***	0.451	-0.937	1.347	0.784	1.096
LTC	2.365**	1.309	1.864*	-0.389	0.617	-1.970**
TRX	1.683*	0.063	-1.360	-0.734	2.071**	-1.798*
LINK	1.521	1.119	-0.830	-0.597	-1.295	-0.328
ETC	0.251	1.579	0.4704	0.162	-1.425	-1.129
Volatility						
ETH	11.16***	9.063***	0.497	-0.484	2.662***	-0.834
DOGE	1.384	-0.581	1.702*	-0.246	1.060	2.085**
BNB	5.927***	2.3008**	-0.226	2.849***	1.131	0.858
XRP	4.293***	1.435	1.188	0.432	0.241	-0.521
ADA	3.794***	2.137**	-0.831*	1.497	0.225	0.589
LTC	9.650***	1.512	0.427	0.692	1.211	-0.406
TRX	5.268***	2.942***	0.434	-1.260	3.152***	1.566
LINK	2.016**	1.627	0.297	1.127	0.739	-0.356
ETC	6.391***	5.784***	0.858	0.032	1.186	1.591
Illiquidity						
ETH	1.050	-0.930	-0.411	-0.228	-0.314	1.752*
DOGE	-1.769*	1.465	1.485	1.353	-0.972	-0.341
BNB	2.543***	0.330	0.034	-0.293	6.689***	2.614***
XRP	0.225	-0.477	-1.211	-0.367	-2.213**	0.534
ADA	-1.211	-0.369	1.121	0.055	0.213	1.117
LTC	-1.238	0.027	-1.582	-2.103**	-0.561	1.431
TRX	-1.431	-1.268	0.734	-1.086	0.481	4.790***
LINK	0.179	-1.692*	-0.441	0.112	-1.663*	-1.831*
ETC	-0.431	1.871*	-2.162**	-0.334	-1.169	-0.698

Notes: This table shows the causality test in the distribution of Candelon and Tokpavi (2016) applied to the left tail (quantiles 0.01, 0.05 and 0.1), right tail (quantiles 0.9, 0.95 and 0.99), and centre of the distribution (quantiles 0.2, 0.3, 0.4, 0.5, 0.6, 0.7 and 0.8). $V_{BTC \to i}$ and $V_{i \to BTC}$ denote the causality statistics from BTC to the altcoins and vice-versa, respectively. The tests were performed using the Bartlett kernel and a truncation parameter $M = 1.5T^{0.3} = 14$. Significance at the 10%, 5% and 1% levels are denoted by *, **, ***, respectively.

For returns, in the left tail, the causality runs from BTC to four altcoins (BNB, LTC, TRX and ETC) but is only significant at the 1% level for BNB. In the centre, causality runs from BNB to BTC, while in the right tail, there is no significant causality at the 1% level. For first difference of the log-volume, most of the causality occurs in the left tail where there are two cases of bidirectional causality (ETH and XRP) at the 1% level. Most of these causalities fade away in the centre and especially in the right tail. The exception is DOGE, in the centre of the distribution, where now the causality from BTC to DOGE is reinforced. Volatility presents a similar pattern but with more positive results. In the left tail, most of causality runs from BTC to the altcoins, with DOGE being the only altcoin without any significant causality. There is bidirectional causality between BTC and ETH, TRX, and ETC. In the presence of bullish markets, there is causality from BTC to ETH and TRX. Illiquidity presents a scarcer number of significant relationships. In the left tail BTC causes BNB, in the centre there is no significant relationship at 1%, and, interestingly, in the right tail, the causality runs bidirectionally between BTC and BNB, and unidirectionally from TRX to BTC.

5.2. Performance of the Trading Strategies

The three trading strategies with the highest Sharpe ratio at the end of the out-of-sample period are the voting system "9 votes", the strategy based on the lagged information of all cryptocurrencies ("All") and the "Dynamic" system. These three strategies are assessed out-of-sample, and the results of their performance are presented in Table 6. This table also presents the results of the strategy based only on BTC information. Clearly, this is a poor strategy providing almost the same results as the B&H strategy.

Although there are mixed results in terms of win rate, certainty equivalent and extreme risk, measured by the VaR, we may claim that the three best strategies outperform the B&H strategy, and the strategy based only on BTC information. Most notably, "All" is the one with the best results in the most important metrics, i.e. Sharpe ratio and Sortino ratio. In all dimensions analysed the "All" strategy beats by far B&H strategy. The "All" strategy provides a cumulative return after transaction costs of 331.4%, while the B&H strategy, with no transaction costs, has a cumulative return of 187.9%. The higher mean return coupled with the lower standard deviation of the "All" strategy provides a Sharpe ratio of 94.59%, which is higher than the Sharpe ratio of the B&H strategy at the 10% significance level. The claim on the superiority of the "All" strategy is reinforced by the Sortino ratio, which achieves a value of 139.7%. The strategy is better suited for investors with low-risk aversion ($\gamma = 1$), although in terms of extreme risk, measured by the VaR, is comparable to the other two best strategies.

Table 6 – Performance of the best three trading strategies after round-trip transaction costs of 0.5% and an entry/exit barrier of ±0.25%

			Best 3 strategies		
	B&H	BTC-s	9 votes	All	Dynamic
Percentage of days in the market	100	83.72	45.43	60.14	63.19
Win rate	51.00	51.35	53.64	52.68	52.48
Cumulative return	187.9	175.0	221.9	331.4	281.1
Annualized mean return	46.31	41.36	38.00	56.40	49.20
Annualized std. deviation	71.54	67.69	50.44	59.63	57.40
Annualized Sharpe ratio	64.74	61.11	75.34	94.59	85.71
Bootstrap p-values against B&H	--	50.19	24.56	9.99	17.98
Bootstrap p-values against BTC	50.10	--	23.56	9.98	17.53
Annualized Sortino ratio	92.01	86.57	113.5	139.7	131.0
Annualized CE with γ = 1	20.04	17.77	25.31	38.07	32.83
Annualized CE with γ = 3	-30.39	-28.22	-0.15	-1.79	0.16
Annualized CE with γ = 5	-63.88	-60.72	-22.93	-39.57	-27.95
CVaR at 1%	14.33	14.30	10.67	12.39	10.98
CVaR at 5%	8.60	8.38	6.59	7.09	7.11

Notes: This table presents the performance of the three best strategies, according to the Sharpe ratio, and compares them with the Buy-and-Hold (B&H) and the active strategy that only uses BTC information (BTC-s). The best active strategies are the Signal ensemble with 9 votes (denoted by "9 votes"), the strategy based on the model forecasts with all information of the 10 cryptocurrencies (denoted by "All") and the strategy that chooses dynamically the best strategy out of the 8 active strategies considered. Besides the relative number of days with an active long position in the market, the strategies are assessed with the following performance metrics: Win rate corresponding to the percentage of days in the market in which the strategy has a positive return, Cumulative return given by the exponential of the of the daily continuous returns of strategy j, $\exp(\sum r_{j,t}) - 1$, annualized mean, annualized standard deviation, annualized Sharpe ratio, assuming that the risk-free rate is zero, bootstrap p-values corresponding to the probabilities of the daily Sharpe ratio of the active strategy are higher than the daily Sharpe ratio of the B&H and of the BTC-s strategies, annualized Sortino ratio which considers in the denominator the downside risk from a target value equal to zero, annualized certainty equivalent of a CRRA (Constant Relative Risk Aversion) utility function with a risk aversion parameter of γ = 1, 3, 5, and the $CVaR_{\alpha\%}$ (Conditional Value-at-Risk at α%) with α% = 1%, 5%. All metrics are computed on returns after round-trip transaction costs of 0.5%. The p-values were obtained using 100,000 bootstrap samples created with the circular block procedure of Politis and Romano (1994), with an optimal block size chosen according to Politis and White (2004) and Patton et al. (2009). All values are in percentage.

Although the strategies are assessed considering a threshold of ±0.25%, which is an obvious figure due to the consideration of round-trip transaction costs of 0.5%, arguably the profitability of the trading strategies could be fostered by optimizing this parameter. Table 7 presents a sensitivity analysis, considering several entry and exit barriers.

Table 7 – Sensitivity of the trading strategies to the market enter and exit thresholds

Thresholds	Statistics	BTC-s	Best of other strategies	All	Dynamic
±0.2%	Rank (#)	(#5)	9 votes (#3)	(#1)	(#2)
	SR (%)	49.83	53.91	84.14	76.79
	p-value	0.753	0.452	0.168	0.263
	Σrt (%)	137.2	158.3	271.9	241.0
±0.25%	Rank (#)	(#7)	9 votes (#3)	(#1)	(#2)
	SR (%)	61.11	75.34	94.59	85.71
	p-value	0.502	0.246	0.099*	0.180
	Σrt (%)	175.0	221.9	331.4	281.0
±0.3%	Rank (#)	(#8)	Median (#2)	(#1)	(#5)
	SR (%)	60.19	102.5	104.6	80.55
	p-value	0.510	0.071*	0.053*	0.220
	Σrt (%)	171.6	399.3	402.0	253.4
±0.35%	Rank (#)	(#8)	10 votes (#2)	**(#1)**	(#7)
	SR (%)	68.75	116.28	**118.28**	70.71
	p-value	0.334	0.046**	**0.016****	0.315
	Σrt (%)	205.7	341.6	**533.7**	214.5
±0.4%	Rank (#)	(#5)	10 votes (#2)	(#1)	(#8)
	SR (%)	91.48	112.2	113.4	60.56
	p-value	0.124	0.054*	0.022**	0.417
	Σrt (%)	328.4	307.7	488.9	178.1
±0.45%	Rank (#)	(#6)	Median (#1)	(#2)	(#8)
	SR (%)	91.01	109.3	107.8	39.31
	p-value	0.127	0.043**	0.037**	0.693
	Σrt (%)	326.4	453.7	434.8	116.1
±0.5%	Rank (#)	(#5)	Median (#2)	(#1)	(#8)
	SR (%)	97.72	102.5	115.3	48.97
	p-value	0.080*	0.072*	0.022**	0.583
	Σrt (%)	373.2	390.3	499.6	139.4
±0.55%	Rank (#)	(#5)	Trim. mean (#2)	(#1)	(#8)
	SR (%)	78.23	91.52	110.39	17.74
	p-value	0.252	0.118	0.036**	0.879
	Σrt (%)	250.6	329.5	445.0	77.46

Notes: This table presents a sensitivity analysis of the trading strategies to the market entry and exit thresholds. Rank refers to the order of the strategy out of the overall 8 strategies (BTC-s, Trimmed mean, Median, 8 votes, 9 votes, 10 votes, All, and Dynamic) according to the Sharpe ratio. SR is the Sharpe ratio, p-value is the bootstrap p-value against

B&H, i.e., the probability of the daily Sharpe ratio of the active strategy, considering all days in the sample, being higher than the Sharpe ratio of B&H strategy that consists of being long all the time (these p-values are obtained using 100,000 bootstrap samples created with the circular block procedure of Politis and Romano (1994), with an optimal block size chosen according to Politis and White (2004) and Patton et al. (2009)) and Σr_t is the cumulative return of the strategy out-of-sample. Significance at the 10%, 5% and 1% levels are denoted by *, **, ***, respectively. The best threshold and best strategy with that threshold are highlighted in bold.

The results point out that the "Dynamic" strategy is highly sensitive to the threshold. With lower thresholds, this is the second-best strategy, but when the threshold increases the performance of this strategy decreases and at thresholds higher than ±0.4% it is ranked as the worst strategy of all. The "All" strategy is always the best strategy, except when the threshold is equal to ±0.45%, however, the difference in the Sharpe ratios between the "All" strategy and the best strategy is only 1.5%. Finally, it seems that the performance of the strategies is a concave function of the threshold value. For the "All" strategy and the best other strategy, the best performance is achieved at an entry/exit barrier of ±0.35%.

6. Conclusion

This paper investigates the information transmission concerning the returns, volumes, volatilities and illiquidity between BTC and the nine altcoins with the highest market capitalization, excluding stable cryptocurrencies and those created after 2018, between November 10, 2017, and December 31, 2022. This was accomplished using causality tests in the mean and the distribution.

Contrary to the claim of several studies (e.g., Koutmos, 2018; Ji et al., 2019), there is no clear dominance of BTC regarding information transmission to altcoins in the mean. In terms of returns and illiquidity, most causality runs in the opposite direction, from altcoins to BTC, which is in line with Bação et al. (2018). In terms of volatility, the causality is mainly bidirectional as claimed by Ji et al. (2019) and Raza et al. (2022). However, BTC shows its superiority in terms of volume.

The causal relationship between BTC and each altcoin is more evident in the left tail of the distributions, except for illiquidity where the right tail stands out, with the transmission of information occurring mainly from BTC to altcoins. On the other hand, at the highest quantiles, causality occurs mainly from altcoins to BTC (except for volume). This agrees with the results obtained by Shahzad et al. (2022).

These results suggest that there is some information transmission from altcoins to BTC, especially at the highest quantiles of the distribution, and this information can be used profitably to trade in BTC. To assess this hypothesis, one used the following procedure: (1) Eleven models were built, with the first one having the BTC series as explanatory variables, nine using the information from BTC and each one of the altcoins considered, and a last one with all series, with a predictor space formed by 280 variables. (2) The forecasts were obtained dynamically day by day using a moving window with a fixed length. Given the high dimensionality of the optimization problem, we resort to LASSO regressions, which allow the selection of the important regressors. (3) Finally, the performance of the trading strategies which use a combination of the forecasts and all the information on the

10 cryptocurrencies was assessed out-of-sample using several metrics and considering round-trip transaction costs of 0.5% and an entry/exit barrier of ±0.25%.

The strategy based only on BTC information has very low performance providing almost the same results as the B&H strategy. Hence, we may conclude that if there is some information in the BTC, this information is not important enough to surpass the transaction costs. The three trading strategies with the highest Sharpe ratio at the end of the out-of-sample period are the voting system "9 votes", according to which the investor enters, stays in, or exits the market if nine of the ten models agree on the signal of the forecasts, the strategy based on the lagged information of all cryptocurrencies and the "Dynamic" system, which chooses step-by-step the strategy that minimizes the MSE (mean squared error) of the previous seven days. The best strategy is the one that uses the information of all cryptocurrencies to forecast, via LASSO, the Bitcoin returns. This strategy provides a cumulative return after transaction costs of 331.4%, while the B&H strategy, with no transaction costs, has a cumulative return of 187.9%, a Sharpe ratio of 94.59%, which is higher than the Sharpe ratio of the B&H strategy at the 10% significance level. The strategy is better suited for investors with low-risk aversion ($\gamma = 1$) with an extreme risk lower than the B&H strategy.

Finally, we tested the sensitivity of the performances to the trading rules on the entry/exit threshold. The strategy with all information presents robust results in the face of varying thresholds, being almost always the best strategy. It seems that the performance of the strategies is a concave function of the threshold value, and hence the profitability of the trading strategies may be fostered by optimizing this parameter.

All in all, probably the most important conclusion to retrieve from this paper is that trading strategies on Bitcoin should consider large sets of predictors, namely the information from other cryptocurrencies. This claim is of outmost important for investors in cryptocurrencies.

Based on the results presented here, future work may be developed considering an expanded sample of cryptocurrencies, using machine learning models, and optimizing the parameter of transaction trigger.

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Economic Vote: Portugal in the first two decades of the 21st century

Voto Económico: Portugal nas duas primeiras décadas do século XXI

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ABSTRACT
This paper examines how local economic conditions influenced government voting shares in the first two decades of the 21st century, using a panel consisting of 278 municipalities across six elections. Firstly, the statistical irrelevance of the socio-demographic variables on the incumbent electoral fortune can be highlighted. The results show that higher local unemployment reduces government vote shares, consistent with the responsibility hypothesis. Surprisingly, however, income growth appears to hurt incumbents, a result found to be exclusive to municipalities where national and local governments are politically aligned. Evidence suggest that this unexpected outcome may stem from the lingering effects of Portugal's financial crisis and austerity measures, in which drastic cuts were initially made to incomes, leaving voters feeling dissatisfied and viewing later increases in income too small to reestablish the lost purchasing power.
Keywords: Local economy, Elections, Portugal, Economic Vote.

JEL Classification: D72; H7

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1. Introduction

Understanding the reasoning behind voting behavior is important for a better knowledge of how well democracy operates and the links that are established between the political and socio-economic spheres. In an economic perspective, this paper analyzes voting decisions in Portuguese legislative elections during the first part of the XXI century.

Historically, voting theories are linked to each other, as they have developed from each other, either as a complement or as a critique. The pioneering works of Downs (1957) and Campbell et.al. (1960) presented two distinct views on the subject, multiplying the debate around the motivations and consequences of voting and constituting the foundations on which most of the literature was developed. Campbell et.al. (1960) viewed voting behavior in the individual's living spaces and groups, giving rise to the posterior sociological literature on the subject. Downs (1957) introduces a utilitarian reflection on the process of electoral choices, assuming that voters are relatively immune to the social context and able to establish their preferences through a cost-benefit analysis (well-being maximization), in practical terms very similar to that of economic choices (see also Riker and Ordeshook, 1968). This is commonly called the instrumental model, and over the years evolved into a prolific branch of literature, from where economic vote emerged[1].

The economic view of electoral behavior is essentially supported by the close connection between economic conditions and the well-being of the populations. The main assumption, called the responsibility hypothesis, states that governments delivering good economic conditions are rewarded in the ballots, while those that do not are electorally penalized. As we can witness, the economy is perhaps the most highlighted topic during electoral campaigns. Growth, wages, deficits, unemployment and inflation are among the issues most referred to by the media, politicians and by overall commentators. These variables are also the most used by researchers when specifying government voting through an empirical test function. Since the early works of Mueller (1970), Goodhart and Bhansali (1970) and Kramer (1971) two explanatory dimensions are defined in this function, one economic and another political. The voting function has been tested over time, and for many countries with great success, but instability in these two dimensions has been the most prevalent feature of the results found (for surveys see Paldam, 1991; Nannestad and Paldam, 1994; Paldam, 2003). The importance of economic variables in studies with aggregate data has generally been confirmed[2] , in particular the negative reaction of voters to increases in unemployment and inflation.[3] Voting functions are the extrapolation of the idea that the decision to vote should not be based purely on personalities, party affiliation or chance, seeking to find economic reasons for changes voting patterns, particularly tied to swing voters.

In Portugal, the economic perspective of politics has been studied in various angles, being the government vote function one of those (see Veiga et. al. 2024, for a recent survey

[1] For more details on the evolution of the various strands of the voting literature see Evans (2003) chapters 3, 4 and 5. For the evolution of economic voting see also, from the same book, chapter 6.

[2] Paldam (2003).

[3] In certain cases, multicollinearity concerns may be raised, but normally the Phillips curve is weak enough to allow the simultaneous inclusion of unemployment and inflation, or instead of unemployment income is used confirming Okun's law.

on the broader subject). As to economic voting, Veiga and Veiga (2010) and also Martins and Veiga (2014) analyze legislative elections and the government's results with municipal data. Both studies found that local and national economic conditions are important, and both confirm the responsibility hypothesis.[4] Also, when dealing with Portuguese municipal elections, Martins, and Veiga (2013) found that the performance of the national and local economy are important for mayors voting results, especially if local governments are of the same party as the central government. The municipal economic conditions are also relevant, particularly in scenarios where voters perceive more clearly the responsibility of the local government. To sum up, the responsibility hypothesis is well established in the literature that examines voting behavior in Portugal. Nevertheless, changes in the first two decades of the XXI century, like the massification of the internet, the appearance of social media platforms, and technological advances like, for instance the smartphone, renew the interest on the accountability mechanism and on economic voting in general. Furthermore, Portugal faced a significant and persistent economic crisis in the second decade of this century.

All these new and important events beg the question as to what may have changed (if anything) in the way the economy affects government vote shares. This is the basic motive for restricting our sample only to the XXI century. As such, the objective of this paper is twofold. First, investigate the national government voting function and its determinants in more recent years, thus complementing and updating the existing studies for Portugal. Second, test the socio-demographic dimension, usually not included in economic vote functions for Portugal, and contrast our results with those found previously, knowing that our timespan encompasses a highly specific and important context (major technological innovations and a deep lingering crisis). And indeed, our results show that some things stayed the same, but others changed. To execute the intended analysis, an extensive database of economic, socio-demographic and political data from the 278 mainland municipalities of Portugal were collected, for the six legislative elections that took place over the first 20 years of the XXI century.

The rest of the article is organized as follows. Section 2 presents the data and model and gives a brief description of the Portuguese electoral system. The empirical results are presented and discussed in Section 3. Finally, Section 4 concludes.

2. **Data and Model**

Portugal has a multiparty system, with the Assembly of the Republic serving as its unicameral parliament. It consists of 230 deputies elected every four years through direct suffrage. Political parties submit closed and blocked candidate lists in each district, and seats are allocated proportionally by district using the Hondt method. The legislative elections determine the formation of the national government. Despite the multiparty nature of the system, all Portuguese governments have been led (in majority or in coalition) by two main parties: the center-left Socialist Party (PS) and the center-right Social Democratic Party

[4] Other studies, using popularity functions for Portugal, validate the accountability hypothesis (Veiga and Veiga, 2004a, 2004b).

(PSD). Table A.1 of the Appendix provides some summary information about the elections that took place in Portugal during the covered timespan, namely the ruling government, national percentages, PM and type of government.

The basic empirical model is characterized by equation (1), where the dependent variable is defined as the ratio of votes obtained by the governing party divided by the total valid votes (in percentage) per mainland municipality[5] $VGOV_{it}$, in the legislative elections that took place in year t.

$$VGOV_{it} = \beta_0 + \beta_1 ECO_{it-1} + \beta_2 SOCIAL_{it} + \beta_3 POL_{it} + \delta_t + \gamma_j + u_{it} \quad (1)$$

$$i = 1, ..., 278; \text{t} = 2002, 2005, 2009, 2011, 2015, 2019; j = 1, ..., 18$$

where ECO_{it-1} is a vector of economic variables, lagged one period. Nobody knows the value of current economic variables at the time of the election. $SOCIAL_{it}$ represents the set of sociodemographic variables in line with those generically used in the literature. We also include a set of political variables, POL_{it}. The model includes controls for temporal and territorial idiosyncrasies by adding δ_t that represents a *dummy* variable for each election year t, and, since votes are converted into seats at the district level, we also include γ_j a *dummy* for each of the 18 mainland districts, j. The u_{it} is the error term with the usual proprieties.[6]

The electoral data were obtained from the General Secretariat of the Ministry of Internal Affairs (*Secretaria Geral do Ministério da Administração Interna*). Economic variables are difficult to find at the municipal level and simultaneously exhibiting time consistency. The variables used to measure unemployment consist of the monthly average number of registered unemployed (*Unemployment*), from the Institute of Employment and Vocational Training (IEFP) and the unemployment rate that is provided by INE. The INE unemployment rate is available at the municipal level only in census years. Thus, it was decided to construct a proxy using the methodology adopted by the same institute for a variable available in its database, called Registered unemployment per 100 *inhabitants aged 15 or over*[7] (by NUTS III – *Unemployment rate*). Income, in turn, is measured through two different indicators from INE. The first variable is the per *capita* Purchasing Power Index by municipality (*Purchasing Power*)[8]. The second, corresponds to the real Average Monthly Earnings of employees per municipality, in euros (*Average monthly earnings*) used in log form.

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[5] The exclusion of municipalities from the Autonomous Regions of the Azores and Madeira, is because they have specific elections that elects an autonomous government structure. Also, they are less dependent in policy decision making from the central government. Legislative elections under analysis took place in 2002, 2005, 2009, 2011, 2015 and 2019.

[6] Descriptive statistics for the full set of variables used can be found in table A.2 of the Appendix.

[7] The formula is the quotient between the monthly average of the number of unemployed registered by municipality (the first unemployment variable presented) and the resident population aged 15 or over. INE (2021) Registered unemployment per 100 inhabitants aged 15 and over (%).

[8] Consists of an index that measures the relative purchasing power of the municipality. The base corresponds to Portugal (NUTS I). Its periodicity is biennial available for the years 2000, 2002, 2004, 2005, 2007, 2009, 2011, 2013, 2015, 2017 and 2019. The data for the missing years were calculated using a simple arithmetic average between the immediately preceding year and the one immediately following the respective missing year.

The sociodemographic control variables were collected from the National Institute for Statistics (INE, Instituto Nacional de Estatística). These allow the capturing of effects associated with the social and demographic features of the population residing in the municipalities. To avoid endogeneity issues, the size of the municipality is captured by a variable constructed assuming integer values between 1 and 4 according to its size (from bigger to smaller municipalities – *population*)[9]. Age is controlled by including the percentage of the resident population aged 65 years or older (*Pop. over 65*). Regarding education, there is no annual data per municipality for indicators of this dimension, so it was decided to use a *proxy variable* to control the population with secondary or higher education. The services sector (tertiary) is essentially composed of a population with higher levels of education, and the use of employment in the services sector is a good approximation to the population with secondary or higher education by municipality. Nevertheless, it also can be viewed as a proxy for the degree of development of the municipality. In view of the absence of this data at the municipal level, NUTS III aggregation was used (*Employment tertiary sector*).

As for the political dimension, a *dummy* was constructed to identify the municipalities whose mayors belong to the main party in government (*Simultaneous ruling*). Simultaneous governance acquires particular importance in explaining the vote for two reasons. On the one hand, it can capture the party reservation effect, identifying the municipalities in which the party in government traditionally has more support. On the other hand, as Veiga and Veiga (2010: 1729) point out, the simultaneous holding of executive power by a party, either in government or in local authorities, materializes in a greater capacity to manipulate local economic conditions to increase electoral support. In this way, it is expected that the coefficient will be positive and that it will largely affect the votes in government. Veiga and Veiga (2010) point out, however, that voters may have a preference not to concentrate on the national executive power in the same party that controls the respective municipalities, so a negative coefficient of this variable is also possible. In addition, the measure for the effective number of parties (ENP), proposed by Laakso and Taagepera (1979), was constructed, capturing the effects of party fragmentation and competitiveness by district (electoral circle).

Finally, we want to clarify the absence of the lagged dependent variable from the function. Given the democratic alteration the autoregressive component often does not correspond to the votes for the party in power, so we are not in the presence of the traditional lagged dependent variable; as such it has a highly problematic interpretation, and most likely, does not create an omission variable bias problem.

3. **Empirical Results**

Considering the specificities of using panel data, we did standard testing to our model to obtain the appropriate estimator. The *Hausman test* and *F-test* were conducted and pointed to *pooled* OLS being the most appropriate estimator (probably because the district dummies already capture the relevant fixed effects). The results of the tests are presented in table A.3

[9] Population categories: 1 – Lisbon and Porto; 2 – Other municipalities with a population above 40000 inhabitants; 3 – Municipalities with a population between 10000 and 40000; 4 – Other municipalities.

of the appendix. Regarding heteroscedasticity, *Breusch-Pagan/Cook-Weisberg* tests were performed for the different regressions, and confirmed the homoscedasticity hypothesis, thus OLS standard errors are used since they are the most efficient.

Table 1 presents the estimations of the base model with the above-mentioned alternative economic variables. The first two columns include the economic variables lagged one year, while, in columns (3) and (4), those variables are replaced by their average value in the two years prior to the election. This averaging is intended to evaluate the relevant time horizon in the gathering of economic information by the voter[10].

Table 1. Effect of the local economy on government votes – Pooled OLS

Variables	Previous year		Two years prior		no ENP
	(1)	(2)	(3)	(4)	(5)
Unemployment rate (-1)	-0.424***		-0.460***		-0.419***
	(-2.613)		(-2.810)		(-2.581)
Purchasing Power (-1)[a]	-0.031**		-0.029*		-0.036**
	(-2.061)		(-1.923)		(-2.415)
Unemployment (-1)		-0.546***		-0.588***	
		(-2.912)		(-3.110)	
Average monthly earnings (-1)[b]		-5.628***		-5.795***	
		(-2.912)		(-2.981)	
Population	-0.199	-0.034	-0.175	-0.044	-0.182
	(-0.424)	(-0.079)	(-0.374)	(-0.102)	(-0.388)
Pop. over 65	0.013	0.008	0.007	0.003	0.036
	(0.208)	(0.131)	(0.116)	(0.045)	(0.614)
Employment tertiary sector	-0.023	-0.014	-0.025	-0.013	-0.027
	(-0.644)	(-0.385)	(-0.689)	(-0.370)	(-0.764)
Simultaneous ruling	7.891***	7.861***	7.895***	7.872***	7.890***
	(17.465)	(17.434)	(17.478)	(17.468)	(17.456)
Effective Number of Parties	-0.871	-0.778	-0.873	-0.749	

[10] The relevance of the temporal controls and the district *dummies* were tested using a Wald test that confirmed the joint significance of these variables (omitted from table 1 for reasons of space)

Variables	Previous year		Two years prior		no ENP
	(1)	(2)	(3)	(4)	(5)
	(-1.542)	(-1.380)	(-1.544)	(-1.328)	
Constant	43.361***	77.762***	43.399***	78.962***	40.996***
	(13.240)	(6.035)	(13.284)	(6.105)	(14.160)
Obs.	1,390	1,390	1,390	1,390	1,390
Elections	5	5	5	5	5
Adjusted R-squared	0.412	0.414	0.412	0.415	0.411
Election dummies	YES	YES	YES	YES	YES
District dummies	YES	YES	YES	YES	YES

Notes: t statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1;
[a] Variable measured *per capita*.
[b] Variable in logarithm.

The first note goes to the fact that none of the socio-demographic variables used here are statistically significant. We did experiments replacing these variables by others, but the sociodemographic dimension remained statistically irrelevant[11]. As for the political variables, the ENP is not statistically important, but simultaneous governance has a very significant impact on government votes. In municipalities where the mayor is of the same party as the national incumbent, the national government obtains 7.89 p.p. more, *ceteris paribus* (*c.p*). As discussed earlier this is not unexpected, probably capturing much of the effect of the captive votes (non-swing voters) of the party in office.

As to the economy, in general, the results suggest that voters, when collecting economic information, go back a little further in the past than is traditionally found, as the two years of economic performance are relevant for defining the vote percentage of the incumbent. This indicates that the Portuguese voter of the XXI century seems to be less myopic than the one reported in the past literature (see Paldam 2003). For Portugal, Martins and Veiga (2013) report this phenomenon, while most studies don't carefully address the issue. However, Veiga and Veiga (2004a) clearly show that the Portuguese voter looks much more to the present and recent past (retrospective) than to the future (prospective) when incorporating economic information in the voting function. The responsibility hypothesis states that voters tend to reward governments that improve economic conditions, particularly when unemployment is reduced, and income rises. The results presented confirm this assumption for unemployment, as in column 1, an increase of 1 *p.p.* (percentage point) in the unemployment rate causes a

[11] The population size was swapped by the population density. As for the pop. over 65 we, alternatively, used the percentage of residents between 20 and 34 years, and finally the percentage of people working on the tertiary sector were replaced by the percentage in the primary sector. Results are available upon request.

reduction of 0.42 p.p. in votes for the incumbent. The negative effect is corroborated in column (2), where an alternative measure of unemployment is used (Unemployment). However, the responsibility hypothesis is rejected when we look at the effect of income. Increases in both the Purchasing Power and the Average monthly earnings reduce government vote. At first, we suspected that probably the effective number of parties, could be endogenous, since it was constructed including the values of the dependent variable. An instrumental variables model was used to assess the existence of endogeneity, using the lags of the variable itself and measures of lagged population size[12]. Results were inconclusive, presenting different coefficients in sign and amplitude from those in the base estimate, column (1). Considering that this variable does not have statistical significance in most regressions, its extraction from the model does not considerably alter the results of the estimates, as can be seen by comparing the models of columns (1) and (5).

In the literature examining government voting for Portugal (cited previously) the negative effect of income and also of inflation is clearly dominant, with some cases of statistical insignificance, but, as far as we know, such a robust positive effect has never been found. So, the big mystery here is the origin of our results for the income variables. To investigate this, on the one hand, we evaluated the influence of simultaneous governance, and on the other hand, we observed the specific effect of each election. The process was one of interacting both types of dummies with the income variables. The results are presented in table 2, were *SR* is the abbreviation for Simultaneous ruling. From the several estimations with the full set of temporal dummies the one that stood out was the 2015 election. As such that is the only case presented on the table[13].

Table 2. Effect of the local economy on government votes – Pooled OLS

Variables	*per capita* Purchasing power			Average monthly earnings		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate (-1)	-0.415**	-0.401**	-0.384**	-0.449***	-0.437***	-0.428***
	(-2.567)	(-2.483)	(-2.396)	(-2.767)	(-2.715)	(-2.660)
Purchasing Power (-1)[a]	0.006	-0.019	0.031			
	(0.299)	(-1.239)	(1.605)			
Purchasing Power * *SR*	-0.068***		-0.087***			
	(-3.427)		(-4.347)			
Purchasing Power * δ_{2015}		-0.119***	-0.143***			

[12] All the instruments used are correlated with the instrumentalized variable, considered not weak by the weak instrument test and valid by the Sargan test.

[13] Interactions can potentially generate multicollinearity problems. A comparison was made between the coefficients presented in Table 2 and estimates with the economic variables centered, concluding that the coefficients and respective standard errors do not change, allowing a reliable analysis. Results are available upon request.

Variables	*per capita* Purchasing power			Average monthly earnings		
	(1)	(2)	(3)	(4)	(5)	(6)
		(-4.169)	(-4.955)			
Average earnings (-1)[b]				-3.680	-2.755	0.743
				(-1.629)	(-1.360)	(0.308)
Average earnings * *SR*				-4.698*		-7.502***
				(-1.683)		(-2.655)
Average earnings * δ_{2015}					-15.978***	-17.929***
					(-4.466)	(-4.919)
Population	-0.198	-0.349	-0.379	-0.071	-0.077	-0.136
	(-0.424)	(-0.747)	(-0.816)	(-0.164)	(-0.178)	(-0.315)
Pop. Over 65	0.019	0.026	0.037	0.004	0.018	0.023
	(0.310)	(0.437)	(0.617)	(0.072)	(0.296)	(0.375)
Employment tertiary sector	-0.024	-0.019	-0.019	-0.014	-0.014	-0.014
	(-0.681)	(-0.530)	(-0.553)	(-0.388)	(-0.387)	(-0.393)
Simultaneous Ruling (SR)	13.114***	7.826***	14.507***	39.366**	7.752***	58.044***
	(8.251)	(17.416)	(9.063)	(2.103)	(17.282)	(3.063)
Effective Number of Parties	-1.030*	-0.744	-0.921	-0.825	-0.675	-0.740
	(-1.823)	(-1.322)	(-1.643)	(-1.462)	(-1.203)	(-1.321)
Constant	40.825***	42.074***	38.562***	64.867***	58.284***	34.945**
	(12.205)	(12.866)	(11.519)	(4.305)	(4.300)	(2.166)
Obs.	1,390	1,390	1,390	1,390	1,390	1,390
Elections	5	5	5	5	5	5
Adjusted-R^2	0.417	0.419	0.427	0.415	0.422	0.425
Electoral dummies	YES	YES	YES	YES	YES	YES
District dummies	YES	YES	YES	YES	YES	YES

Notes: t statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1;
[a] Variable measured *per capita*
[b] Variable in logarithm.

As to the interactions of the income variables with the dummy capturing simultaneous ruling (columns 1 and 3), results are clear and even more at odds with conventional expectations; the negative effect on government voting is exclusive of those municipalities with this feature, where the clarity of responsibility is higher. This could be capturing a wide range of government policies that affect income positively but with a distribution of income among the population that voters do not appreciate. Also, there were very turbulent economic times in Portugal during the second decade of the timespan in analysis, and when we did the interactions with the electoral dummies, what clearly stood out was the 2015 election (the only presented here, in columns 2 and 4). The year of 2015 marks the end of a legislature dominated by the austerity policies, applied as part of the third financial bailout of Portugal by the so-called Troika (European Central Bank, European Commission and International Monetary Fund), and the consequent reduction in real household income. For the 2015 executive in office (coalition Pàf), all things constant, a one-point increase in the purchasing power index reduced, on average, the percentage of votes obtained between 0.119 *p.p.* and 0.143 *p.p.* (columns 2 and 3) when compared to all other elections. Having been a mandate deeply marked by austerity policies, and weak economic growth, it is reasonable to assume that, as for the simultaneous government, voters in municipalities with a higher level of income, and higher levels of education, sought to punish the PSD/CDS-PP coalition for the policies adopted. The bailout period was long, and in the beginning, the Portuguese government reduced significantly people's income. So even with posterior increases in income the prior purchasing power of the population was not achieved for many years. As such, the overall conclusion we can derive from Table 2 is that, probably, the negative income result relates fundamentally with the effects of the crises that hit Portugal in 2009/10 with devastating economic and social effects that prolong themselves many years[14]. The initial loss of purchasing power was so severe that increases in income were probably viewed by voters as too small and actually penalized the government.

4. Conclusion

The purpose of this work was the empirical analysis of the government voting function for Portugal in the first two decades of the twenty-first century, with an emphasis on the influence of the economic dimension. An extensive panel data was constructed for the 278 mainland municipalities, spanning between 2000 and 2019, that included six elections.

The results obtained revealed some interesting particularities. The first note goes to the statistical irrelevance of the extended socio-demographic variables used. Typically, they are absent from government voting functions for Portugal, and also in general. This finding deserves further study since, traditionally, it is an important dimension in the literature that examines party voting and turnout. In Municipalities where the local incumbent is of the same party as the national government, vote shares for the latter are significantly improved. This is probably related to two potential simultaneous effects. The first, capturing much of the effect of the captive votes (non-swing voters) of the party in office at the municipality;

[14] Some extraordinary measures taken at the time remained in place, some at least until 2020, such as the increase in VAT on energy for instance.

and the second, it is easier for national governments to improve economic conditions locally when the municipal and the national incumbency are politically aligned.

The core purpose of the paper was to analyze the effect of the local economic conditions on the government's electoral fortune during the first two decades of this century. We found some surprising results, along with others in line with the literature on the subject and with the responsibility hypothesis. First, the local economy, as a whole, shown to be an important explanatory dimension of government results. Also corroborating the main findings of the literature, the variables that were used to measure unemployment proved to behave as predicted by the responsibility hypothesis; Increases in local unemployment have a negative impact on the vote shares of Portuguese governments. These results align themselves with the previous literature that studied the XX century in Portugal. However, in the analysis carried out here, the coefficients on the variables measuring income assumed negative values, a result at odds with what was expected and what is typically found for Portugal. We dig deeper in trying to understand why the responsibility hypothesis here was reversed, i.e. increases in income reducing government vote shares. We evaluated the influence of simultaneous governance and observed the specific effect of each election. The process was one of interacting both types of dummies with the income variables. As to simultaneous ruling, results were clear and even more at odds with conventional expectations; the negative effect on government voting is exclusive of those municipalities where municipal and national governments are politically aligned (where the clarity of responsibility is higher). Furthermore, when we did the interactions with the electoral dummies, what stood out was the 2015 electoral dummy. That year marks the end of a legislature dominated by the austerity policies, applied as part of the third financial bailout of Portugal. When these two findings are put together, they reveal a possible explanation for the income result found. The legislature that ended in 2015 started with a new Portuguese government forced to heavily reduce people's income and was marked by weak economic growth that persisted for a very long time. So, even with posterior increases in income the prior purchasing power of the population was not achieved for many years. The initial loss of purchasing power was so severe that increases in income were probably viewed by voters as too small and too late and actually penalized the government. As such, the overall possible conclusion we can derive is that the negative effect of income on governments electoral results is a consequence, fundamentally, of the crises that hit Portugal in 2009/10 with devastating economic and social effects that prolong themselves for many years, even after 2015. These findings challenge conventional voting models and highlight the complex interplay between economic conditions, political alignment, and electoral accountability.

Finally, the results suggest that XXI century Portuguese voters go a bit further back in time when evaluating the government's economic performance, than most of the literature advocates. Nevertheless, this inference is only slightly explored here, but deserves a more detailed analysis and further research.

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Appendix

Table A.1. Legislative elections in Portugal: 1999-2019

Elections	Winning Party	% Members elected	Premier	Type of Government
10/10/1999	PS	50.0	António Guterres	Minority
17/03/2002	PSD	45.7	Durão Barroso	Coalition (CDS-PP)
20/02/2005	PS	52.6	José Sócrates	Majority
27/09/2009	PS	42.2	José Sócrates	Minority
05/06/2011	PSD	47.0	Passos Coelho	Coalition (CDS-PP)
04/10/2015	PàF[1]	46.5	Passos Coelho	Coalition (CDS-PP)[2]
06/10/2019	PS	47.0	António Costa	Minority

Notes: [1] PàF (Portugal à frente – "Portugal Ahead") was composed of PSD and CDS-PP (pre-electoral coalition).
[2] Rejection of the Government's program in Parliament. PS takes over the government with the parliamentary support of the BE and the CDU.
Source: National Elections Commission (CNE)

Table A.2. – Descriptive statistics

Variable	Aggregation	Obs.	Average	Std. Deviation	Min.	Max.
Gov. Vote shares	Municipality	1668	36.113	10.302	8.242	77.454
Unemployment (% pop.)	Municipality	1390	4.211	1.611	.922	10.990
Unemployment rate	Municipality	1390	4.874	1.898	1.041	12.758
Purchasing Power	Municipality	1665	75.775	23.534	34.950	277.930
Average monthly earnings	Municipality	1390	833.272	152.043	581.687	1953.080
Population	Municipality	1668	3.098	.779	1.000	4.000
Population density	Municipality	1668	309.102	859.179	3.800	7740.500
Pop. 65 plus years	Municipality	1668	23.454	6.526	8.717	46.271
Pop. between 20 and 34 years old	Municipality	1668	17.987	2.850	9.190	26.780
Employment Services Sector	NUTS III	1668	55.473	11.622	32.065	86.255
Employment, Primary Sector	NUTS III	1668	18.500	11.740	1.094	47.148

Simultaneous Government	Municipality	1668	.423	.494	0.000	1.000
Effective Number of Parties	District	1390	3.504	.686	1.921	5.621

Tabela A.3. Model Selection Tests

	Stat.	P-Value
Hausman (RE vs FE)	114.39	0.0000
F (Pooled vs FE)	0.80	0.9878

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Green Investment Strategies and Financial Performance: Evidence from Portuguese Firms

Estratégias de Investimento Verde e Desempenho Financeiro: Evidência das Empresas Portuguesas

Pedro Alçada

ABSTRACT
This study analyses the relationship between environmental investment strategies and the financial performance of Portuguese companies engaged in the extractive, manufacturing, and utility sectors between 2010 and 2021. According to the results, there is no statistically significant correlation between financial performance and green investment. This outcome is in line with part of the literature suggesting that, in highly regulated sectors, environmental investments are often driven by compliance requirements, acting as risk mitigation measures rather than direct sources of profit. Additionally, short-term metrics like ROA could miss benefits in the long run. On the other hand, eco-innovations have a favourable correlation with both financial performance and, to a lesser extent, green investment.
Keywords: Green Investment, Green Innovation, Financial Performance, Climate Changes.

JEL Classification: G32; Q56; O33; M14; C33

1. Introduction

Climate change is seen as a threat to society, the environment and world economies, both now and in the future, thus threatening sustainable development (Borrego et al., 2010). To answer these challenges, many organizations are actively seeking to adopt new measures (e.g. green investments and green innovations) aimed at environmental protection and promoting an ecological transition (Ye and Dela, 2023).

Several studies have explored the relationship between environmental investments, financial performance, and eco-innovations across various countries, reaching different conclusions. In Indonesia, for example, Chariri et al. (2018) found that green investments enhance firms' reputations and financial performance by demonstrating environmental responsibility. In Italy, Vasileiou et al. (2022) demonstrated that the financial impact of green innovations varies depending on the type of innovation. In Ireland, Siedschlag and Yan (2023) concluded that green investments generally have a positive effect on firm performance, although not all companies benefit equally.

However, to the best of our knowledge, there has been no comparable empirical study focusing on Portuguese firms. This gap is noteworthy given recent indicators (European Commission, Directorate-General for Research and Innovation, 2024) that show Portugal lagging behind European averages in environmental performance and eco-innovation. Additionally, criticism of the National Climate Law's ambition may reflect a broader lack of strategic commitment to environmental issues among Portuguese firms. This context highlights the need to investigate how environmental strategies relate to financial performance in Portugal.

This study employs survey-weighted linear and logistic regression models to explore the relationship between green investment and firms' financial performance, supported by robustness checks based on alternative model specifications. The analysis focuses on Portuguese firms in the extractive, manufacturing, and utilities sectors from 2010 to 2021, using data from the *Enterprises Survey on Environment Protection and Management* (IEGPA).

The paper is organized as follows: Section 2 presents the theoretical framework and research hypotheses; Section 3 describes the dataset, variables, and empirical models; Section 4 reports the main findings; and the final section concludes the study.

2. Theoretical Background and Research Hypothesis

2.1. Green Investment and Financial Performance

According to Eyraud et al. (2013), green investments are those required to lower emissions of air pollutants and greenhouse gases (GHG) without appreciably lowering the production and consumption of non-energy products. On the other hand, financial performance is understood as the way in which a business can generate earnings and growth (Selvarajah et al., 2018).

In line with legitimacy theory, companies actively seek out ways to create and defend their legitimacy by coordinating their policies, goals, and beliefs with those of the community (Chariri et al., 2018), while having the stakeholder interests included in the implementation of strategic decisions, as per stakeholder theory (Indriastuti and Chariri, 2021). Given the importance of environmental preservation in today's society, green investments can be seen as a way for businesses to earn and secure stakeholders' trust and support (Ye and Dela, 2023) as well as legitimacy in the eyes of their communities. Consequently, businesses' willingness to handle climate-related issues can be viewed as a means of enhancing their financial performance.

Although the above-mentioned factors suggest that firms' financial and environmental performance may move in harmony, some research (e.g. Lankoski, 2010) has pointed to the fact that there may be a drawback to the relationship between financial performance and green investment. Among the drawbacks mentioned is the fact that an organization's environmental performance may lead to higher production costs and lower productivity as a result of the implementation of new green technologies and procedures. Consequently, how companies' environmental performance will impact their financial performance is still undetermined and needs additional analysis.

In addition to legitimacy and stakeholder support, green investments may also influence firm productivity through multiple channels. On one hand, they can lead to gains in operational efficiency, such as reduced energy consumption, improved resource management, and lower waste generation. On the other hand, these investments often involve high upfront costs, technological uncertainty, and potential disruptions to existing processes, which may temporarily reduce productivity or profitability (Ambec and Lanoie, 2008). This trade-off contributes to the ambiguity in the literature regarding the true financial benefits of green investment and reinforces the need for empirical analysis. Thus, the following hypothesis is proposed:

Hypothesis 1. *Green investment has a positive effect on firms' financial performance.*

The return-on-assets (ROA) value, a financial metric that assesses a firm's profitability in relation to its total assets, will be used to gauge the financial performance of firms (Chariri et al., 2018; Guenster et al., 2011; Khalid et al., 2023). The entire amount of money invested in minimizing environmental impacts will be employed as a proxy for green investments in this study, which will be based on Xie (2020).

2.2. Green Investment and Green Innovation

Green innovation (also known as environmental innovation or eco-innovation) refers to the development or adoption of products, processes, and services that reduce environmental impact or promote sustainability, including measures such as using cleaner energy sources, recycling materials, or reducing emissions (Vasileiou et al., 2022).

As a specific form of technological innovation, green innovation shares the general objective of creating value through the application of new knowledge but distinguishes itself by incorporating environmental concerns into innovation outcomes. According to innovation theory, investment is one of the most influential elements driving a company's capacity to innovate (Solo, 1951). However, innovation is not solely determined by financial input.

As emphasized by the resource-based view (Barney, 1991; Hart, 1995), firms' internal capabilities – such as technical knowledge, managerial routines, and strategic alignment – are crucial to determining innovation potential and implementation.

Although some authors (e.g., Ahuja et al., 2008; Brown et al., 2009) argue that green innovation is often perceived as risky, costly, and uncertain – making it less attractive to investors – others observe a growing alignment between environmental and economic goals, with firms increasingly viewing green innovation as part of their long-term strategy (Zhang et al., 2023). Moreover, green innovation is not a uniform or necessarily capital-intensive endeavour. As Triguero et al. (2013) highlight, many firms engage in eco-innovation through incremental or low-cost organizational and process improvements – such as energy-saving routines or improved environmental management systems – without the need for substantial capital expenditure.

This perspective suggests that the relationship between green innovation and green investment is not automatic or linear. Some firms may innovate with limited financial resources, while others may invest in green technologies for compliance or signalling purposes without developing innovation capabilities. This theoretical ambiguity justifies the need to test the relationship empirically.

Hypothesis 2. *Firms' green investment is influenced by their level of green innovation.*

2.3. Green Innovation and Financial Performance

The discussion of whether it pays for a company to "go green" is something that has become an essential point, especially given the growing concerns surrounding climate change. One of the processes at the core of this discussion is green innovations, as presented above, since, according to Triguero et al. (2013), these are playing an increasingly important role in the green transition of firms so that environmental and financial objectives can be mutually achieved.

Although eco-innovations are an essential tool for firms to establish strategies that lead to sustainable development, the way in which they contribute to firms' financial performance is still uncertain. Thus, with a view to achieving a win-win situation in which green innovations improve financial performance, firms tend to need to evaluate how the adoption of certain innovations can have a positive effect on the financial area (Vasileiou et al., 2022).

Therefore, to ascertain how green innovations affect companies' financial performance, the following hypothesis is suggested:

Hypothesis 3. *Green innovations influence firms' financial performance.*

3. **Methodology and Empirical Analysis**

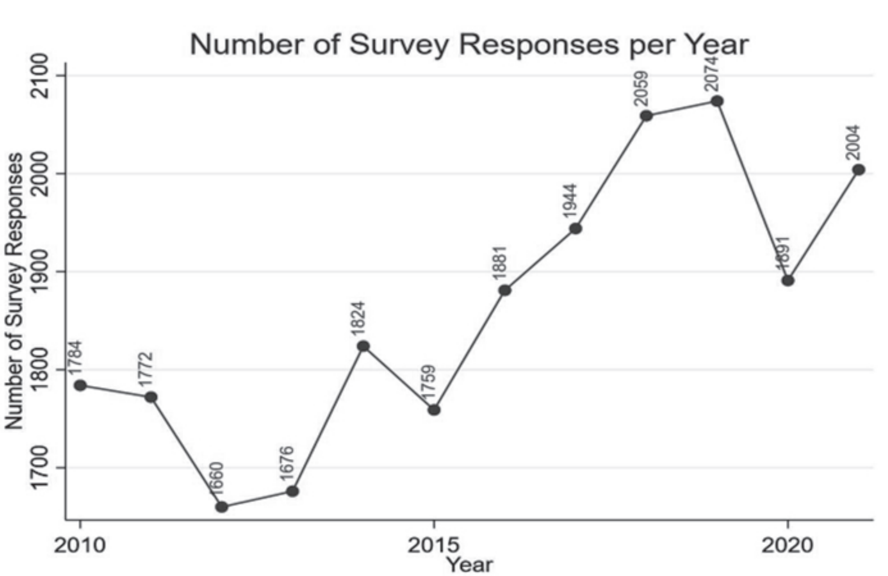
3.1. Dataset

To carry out the empirical analysis in this study, data was used from the *Enterprises Survey on Environment Protection and Management* (IEGPA), conducted annually by Statistics Portugal (INE). This survey contains detailed information on environmental practices, certifications, and investments of Portuguese firms in the extractive industries, manufacturing industries, and electricity, gas, and water production/distribution sectors (according to CAE Rev. 3), covering the period from 2010 to 2021.

To analyse the financial dimension, the dataset was merged with firm-level accounting and financial data from the Integrated Business Accounts System (SCIE), also managed by INE. The linkage was performed using a unique firm identifier common to both datasets, ensuring consistency across years and allowing the construction of a firm-level panel dataset. Our final sample comprises a panel of 6,849 firms with a total of 22,328 firm-year observations. Table A1 in the appendix lists the industries covered by this study and the corresponding summary statistics.

Given the complex stratified sampling design of the IEGPA – based on sector, region, firm size, and turnover class, with exhaustive strata for the largest firms – all estimations were performed using survey-weighted regression methods. The survey's probabilistic and nationally representative nature, along with the calibrated elevation weights provided by INE, ensures that results can be validly extrapolated to the population of Portuguese firms. These standards were employed to weigh each observation, and Stata's svy: module, which appropriately accounts for survey design when estimating coefficients and standard errors, was applied for all regressions. Fixed-effects or random-effects estimators were considered unsuitable due to the cross-sectional nature of the dataset, which only had partial firm rotation. Moreover, traditional panel methods are not directly compatible with design-based weights or the variance structure inherent to complex surveys. Consequently, the most reliable and statistically consistent method for examining the correlations of interest is to employ survey-weighted regressions. Figure 1 presents the number of answers to the survey during the above-mentioned time window.

Figure 1 – Number of survey responses per year



Source: By the author using STATA software based on data from IEGPA, Statistics Portugal.

3.2. Variables

The variables used for the empirical model are described in Table 1:

Table 1 – Description of the variables

Variable	Variable Description
YEAR	Data reference year
NPC	Firm's fictional identification number
CAE	Economic activity (CAE Rev. 3)
ISO14001	Existence of plant with environmental certification according to ISO 14001 standard in the enterprise
EMAS	Existence of plant with EMAS register by Portuguese Environment Agency of the enterprise
GUARANTEE	Existence of financial guarantee of environmental responsibility of the enterprise
GREENHOUSE	Adoption of strategies to reduce emissions of GHG by the enterprise
CARBON	Existence of measures to reduce carbon emissions caused by information and communication technologies (ICT) in the enterprise

OTHERGREEN	Adoption of environmental measures in regular activity of the enterprise
GREENINVEST	Investments in technologies and/or equipment with the purpose of reducing environmental impacts
GRInv	Green investment dummy
RatioInvst	Ratio of green investment to total assets
EBITDA	Earnings before interest, taxes, depreciation, and amortization
ROA	Return on assets
LABOUR	Number of employees
lnTFP	log (total factor productivity)
RLP	Real labour productivity given by the GVA (gross value added) per worker
lnRLP	Log deviation from the industry average RLP for the year
ASSETS	Total assets

The selected productivity measure is the total factor productivity (TFP) at the firm level. The lnTFP is the residual of log production function (i.e. the log difference between firms' output and the weighted sum of inputs). The Levinsohn and Petrin (2003) method was used to estimate the three inputs Cobb-Douglas production function. Labour productivity (LP) was also used to confirm the reliability of the results.

3.3. Models

The first objective of this work is to test the impact of environmental investments on firms' financial performance. To test Hypothesis 1, the following model was created:

$$FP_{it} = \beta_0 + \beta_1 \cdot GREENINVEST_{it} + \gamma \sum ControlVar_{it} + \varepsilon_{it}, \tag{1}$$

where the dependent variable FP_{it} represents the financial performance of the i-th firm in year t using ROA (ratio of EBITDA to total assets) as a proxy (Chariri et al., 2018). The independent variable $GREENINVEST_{it}$ represents green investment of firm i in the year t; $\sum ControlVar_{it}$ represents control variables such as productivity measure and year dummy; and ε_{it} is the error term. To avoid inconsistent results due to the order of magnitude of the variables, the green investment ratio (i.e. the ratio of green investment to total assets, *RatioInvst*) was used. Furthermore, in order to check the robustness of results, two variants of Model 1 are presented: one with TFP, the selected productivity measure, and another with LP.

To check how green investments relate to green innovations, the following logistic regression will be used:

$$P(GRInv = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot greeninov_{it} + \gamma \cdot \sum ControlVar_{it} + \varepsilon_{it})}}, \tag{2}$$

where *GRInv* is a binary variable that takes the value of 1 when the observation encompasses an environmental investment or 0 otherwise, and *greeninov* is an explanatory vector with the variables ISO14001, EMAS, GUARANTEE, GREENHOUSE, CARBON and OTHERGREEN (a description of the variables can be seen in Table 1).

To verify the robustness of the results obtained, the dependent variable was changed from binary one (i.e. GRInv) to a continuous one, the log of *GREENINVEST*, estimating the following model:

$$GREENINVEST_{it} = \beta_0 + \beta_1 \cdot greeninov_{it} + \gamma \cdot \sum ControlVar_{it} + \varepsilon_{it}. \quad (3)$$

Lastly, to assess the effect of the indicators selected to represent green innovations on financial performance, the following model will be employed:

$$FP_{it} = \beta_0 + \beta_1 \cdot greeninov_{it} + \gamma \cdot \sum ControlVar_{it} + \varepsilon_{it}, \quad (4)$$

where the dependent variable FP_{it} represents the financial performance of the *i-th* firm in year t. *greeninov* is an explanatory vector with the variables ISO14001, EMAS, GUARANTEE, GREENHOUSE, CARBON and OTHERGREEN and $\sum ControlVar_{it}$ representing control variables such as the productivity measure and the year dummy.

3.4. Empirical Analysis

According to Siedschlag and Yan (2023), and based on the definition provided in the questionnaire, green investments are defined as the sum of investment (capital expenditures) made in the plant and equipment that enable reductions in pollution or are designed to properly treat waste, noise, wastewater, gas emissions, and other pollutants produced and emitted on firm property. This also covers investments for the enhancement, modification, and adaptation of already-existing equipment and facilities with the goal of preventing, reducing, and minimizing pollution. Taking the previous definition into account, and based on Xie (2020), the value of environmental investment will be used as a measure for the level of green investment.

Three proxies for green investment will be used in this empirical analysis, depending on the models: a continuous variable designated as Investments that encompasses the value of the investment made, a continuous variable designated as RatioInvst that takes the value of the ratio of green investment to total assets and a dummy variable known as GRInv that takes a value of 1 when the observation includes an environmental investment or 0 otherwise. As per Zhang et al. (2023), the natural logarithm of green investment plus one (i.e. $\ln(GREENINVEST + 1)$) is used when employing the continuous variable, in order to ensure the robustness of the empirical findings.

By analysing the survey sample of 6,849 firms, totalling 22,328 observations spanning the period between 2010 and 2021, it is possible to conclude that only 22.13% of the firms made green investments at some point during the period under study (Table 2). While this percentage may appear modest, it reflects structural characteristics of the Portuguese industrial sector, where environmental investment is often driven by regulatory compliance and is not yet widespread across firms. Additionally, the low prevalence underscores the relevance of investigating which factors influence the adoption of such investments.

It is also worth noting that green investment is not evenly distributed over time or across firms. In particular, the year 2011 saw a noticeable spike in the average value of green investments. Upon closer examination, this was driven by three firms with exceptionally large investments. Although these cases are statistical outliers, they were retained in the analysis to preserve the representativeness of the dataset and reflect real-world variation in investment behaviour.

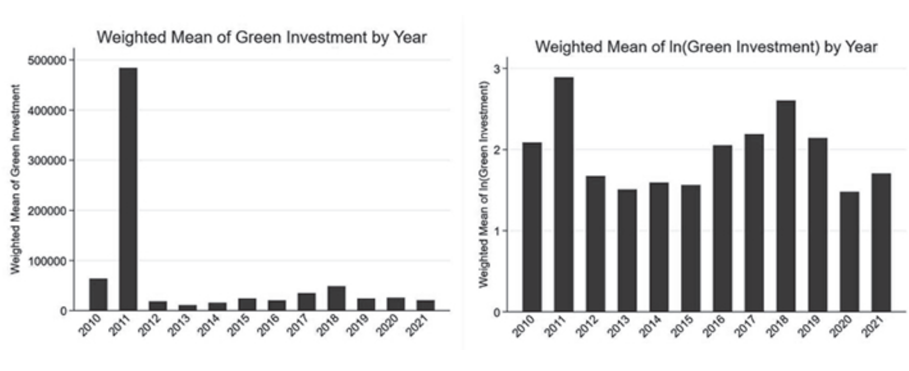
Table 2 – Percentage of green investment

Green Investment (GRInv)	Number of Observations	Weighted Count	Percentage
No (GRInv = 0)	4,835	36,179	77.87%
Yes (GRInv = 1)	2,014	10,281	22.13%

Source: Authors' calculations using STATA software.

The means of the green investments made, and the natural logarithm previously discussed, are shown in Figure 2, appropriately weighted based on the weighting factor. As can be seen in Figures 2a and 2b, green investments peaked in 2011, suggesting that investments were not just substantial overall but also more evenly distributed among the firms under observation. It is also feasible to verify that both average values under review tend to decline after 2018, paying particular attention to 2020 and 2021 as these years display comparatively low values that could potentially be a reflection of the COVID-19 pandemic's effects on green investments, with businesses shifting their financial resources to other domains as a result of financial uncertainty.

Figure 2 – Weighted means of green investment per year



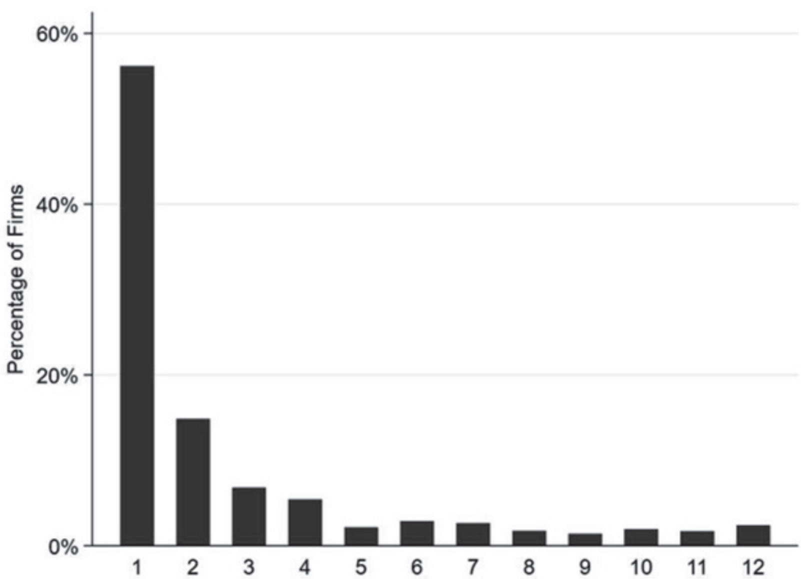
Source: Authors' calculations using STATA software.

As can be seen from Figure 2a, the mean value of green investments peaked in 2011. This is due to the existence of three outliers, that is, three companies made large investments, causing the average in that year to reach a higher investment value compared to the other years under study.

Figure 3 illustrates how frequently green investments occur. Of the firms with green investments included in the analysis, 56% made a single investment over the 12-year span under review, while 15% made two, 7% made three, and 5% made four green investments. This raises a relevant question about whether the frequency or the magnitude of green investments plays a more decisive role in influencing financial performance. From a theoretical perspective, regular investment may reflect a sustained environmental strategy embedded in the firm's operations, while high unique investments may indicate compliance with specific regulations or exceptional innovation efforts.

In the context of this dataset, the majority of green investment activity appears sporadic and concentrated in a small subset of firms. This suggests that, in Portugal, environmental investment is still not a continuous strategic priority for most companies.

Figure 3 – Frequency of firms' green investments, 2010–2021



Source: Authors' calculations using STATA software.

3.4.1. *The Effect of Green Investment on Financial Performance*

The regression results for Model 1, which is used to test Hypothesis 1, are shown in Table 3. As the data on productivity and profitability is only available for the period from 2010 to 2020, the number of observations is reduced in the hypotheses that incorporate financial variables. At the same time, since lnRLP is used as a measure of productivity, we end up with fewer observations because, for some, real labour productivity is less than or equal to zero.

Table 3 – Linear regression for Model 1

Variables	Dependent Variable: ROA	
	Coefficients	
	Model 1: TFP	Model 2: Labour Productivity
Green investment ratio	0.0002 (0.0018)	0.0015 (0.0009)
lnTFP	0.0713*** (0.0110)	——
lnRLP	——	0.1186*** (0.0232)
Constant	0.0939*** (0.0060)	-0.9375*** (0.1949)
Year dummy	YES	YES
No. of observations	20,001	19,717
R^2	0.0184	0.2206

Notes: Standard errors are reported in parentheses. Stars indicate *** p < 0.01, ** p < 0.05, * p < 0.1. (Source: Authors' calculations using STATA software).

The results of the regression for both model specifications suggest that ROA and green investment (RatioInvst) do not display a statistically significant relationship, which does not confirm the hypothesis formulated given that the evidence is not strong enough to draw a definitive conclusion. However, when restricting the analysis to firms that responded to the survey across all years, the results become more statistically significant.

Table 4 – Linear regression for Model 1 with a narrow sample of firms

Variables	Dependent Variable: ROA	
	Coefficients	
	Model 1: TFP	Model 2: Labour Productivity
Green investment ratio	0.4259** (0.1884)	0.2652*** (0.1064)
lnTFP	0.0505*** (0.0027)	——
lnRLP	——	0.0645*** (0.0232)
Constant	0.1369*** (0.0040)	0.0463*** (0.0019)
Year dummy	YES	YES
No. of observations	5,632	5,606
R^2	0.0532	0.2344

Notes: Standard errors are reported in parentheses. Stars indicate *** p < 0.01, ** p < 0.05, * p < 0.1. (Source: Authors' calculations using STATA software).

Looking at Table 4, it can be seen that green investment has a positive and statistically significant influence on the company's financial performance. More precisely, a one-unit increase in the green investment ratio leads to a 43% increase (27% when using LP as a productivity measure) in ROA. This suggests that companies that invest more in environmental initiatives tend to have higher profitability, which is in line with the first hypothesis formulated.

One possible economic explanation for the weak relationship observed between green investment and financial performance lies in the time lag between investment and return. Many environmental investments, particularly in high-impact sectors, involve long-term benefits that may not be reflected in short-term financial indicators such as ROA. Additionally, firms may undertake green investments primarily to comply with environmental regulation or to reduce reputational risk, rather than to increase profitability. In such cases, the investment acts more as a protective measure than a growth strategy.

The R^2 values observed are relatively low, which is not uncommon in firm-level panel data analyses involving highly heterogeneous companies across industries and years. The dependent variable – ROA – is influenced by a wide range of operational, strategic, and market-specific factors, many of which are unobserved or difficult to capture in a survey-based dataset. As a result, explanatory power measured by R^2 tends to be limited in models of this nature. To address potential concerns about model specification, robustness checks were conducted using alternative productivity measures (TFP and LP) and a restricted sample of firms with complete data across the entire period.

3.4.2. *Green Investment and Green Innovation*

To test Hypothesis 2, Model 2 was implemented, and the outcomes are presented in Table 5.

Table 5 – Logistic regression for Model 2

Variables	Dependent Variable: GRInv
	Coefficients
ISO14001	0.273** (0.131)
EMAS	0.776*** (0.307)
GUARANTEE	0.358*** (0.122)
GREENHOUSE	1.389*** (0.165)
CARBON	0.236* (0.136)
OTHERGREEN	0.746*** (0.386)
Constant	-2.811*** (0.393)
Year dummy	YES
No. of observations	22,328
Likelihood ratio chi-square	2470.56
Log pseudolikelihood	-34943.435
Pseudo R^2	0.0341

Notes: Standard errors are reported in parentheses. Stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (Source: Authors' calculations using STATA software).

All the indicators, or independent variables, have positive, statistically significant coefficients, as indicated by the data in Table 5. This suggests that the predictors used as proxies for green innovations represent an increased likelihood of green investments being made. Looking at column (2), it can be said that factors such as owning an EMAS[1]-registered facility granted by the APA-Portuguese Environment Agency (EMAS), having a financial guarantee that allows them to assume the environmental responsibility inherent in their business in accordance with Decreto-Lei nº 147/2008[2] (GUARANTEE), and adopting a strategy to reduce GHG emissions from their business (GREENHOUSE) are powerful arguments for green investment (β_2 = 0.776, β_3 = 0.358 *and* β_4 = 1.389, respectively). More specifically, when firms decide to adopt the green innovation measures, the probability of implementing green investments increases by 117.3% ($e^{0.776}$ – 1), 43.0% ($e^{0.358}$ – 1) and 301.1% ($e^{1.389}$ – 1), respectively.

To confirm the results obtained (Table 5) and ensure the robustness of the data, the dependent variable was changed from GRInv, a binary variable, to lnGI, a continuous variable already presented. The results of the ordinary least squares linear regression with the abovementioned modification are presented in Table 6.

Table 6 – Robustness check

Variable	Dependent Variable: lnGI
	Coefficients
ISO14001	0.480* (0.287)
EMAS	1.314** (0.608)
GUARANTEE	0.439* (0.232)
GREENHOUSE	2.440*** (0.334)
CARBON	0.044 (0.238)
OTHERGREEN	0.642** (0.264)
Constant	0.667 (0.423)
Year dummy	YES
No. of observations	22,326
R^2	0.1215

Notes: Standard errors are reported in parentheses. Stars indicate *** p < 0.01, ** p < 0.05, * p < 0.1. (Source: Authors' calculations using STATA software).

[1] The Community Eco-management and Audit Scheme (EMAS) is a voluntary mechanism that aims to promote the continuous improvement of the environmental performance of organizations through the establishment and implementation of environmental management systems, as well as the provision of relevant information to the public and other interested parties, as per Commission and for Environment (2007).

[2] This decree establishes the Legal Regime of Environmental Responsibility in Portugal, aligning national law with the Environmental Liability Directive (Directive 2004/35/EC) of the European Parliament and the Council. Its aim is to prevent and remedy environmental damage, reinforcing the "polluter pays" principle.

In the robustness check, the only indicator that presents as statistically non-significant is the firm's adoption of measures to reduce carbon emissions caused by information and communication technologies (ICT) which is also the indicator that has the least influence on the decision to go green in the original model.

Therefore, it was found that the indicators associated with green innovations are statistically significant at the usual levels of significance, so the empirical data supports Hypothesis 2.

3.4.3. *Green Investment and Green Innovation*

Table 7 presents the results of Model 3.

Table 7 – Linear regression for Model 3

Variable	Dependent Variable: lnGI	
	Coefficients	
	Model 1: TFP	Model 2: Labour Productivity
ISO14001	-0.0142 (0.0402)	-0.0556* (0.0333)
EMAS	-0.0338 (0.0400)	0.0139 (0.0195)
GUARANTEE	0.0370 (0.0102)	-0.0275** (0.0124)
GREENHOUSE	0.0016 (0.0144)	-0.0035 (0.0107)
CARBON	0.0048 (0.0135)	-0.0124 (0.0109)
OTHERGREEN	-0.0054 (0.0141)	-0.0200* (0.0106)
lnTFP	0.0789 (0.0145)	——
lnRLP	——	0.1186*** (0.0264)
Constant	0.0958*** (0.0129)	0.0539*** (0.0104)
Year dummy	YES	YES
No. of observations	20,000	19,716
R^2	0.0218	0.2439

Notes: Standard errors are reported in parentheses. Stars indicate*** p < 0.01, ** p < 0.05, * p < 0.1. (Source: Authors' calculations using STATA software).

Upon analysis, it appears that most of the green innovation indicators considered are not statistically significant, and the only one that is statistically relevant has a minimal effect on ROA, our dependent variable (β_3 = -0.037 for the first specification of the model and β_3 = -0.0275 for the second), which shows that the adoption of specific measures to mitigate environmental problems does not seem to benefit the profitability of Portuguese companies.

The lack of a clear impact of green innovation on financial performance may stem from several structural and contextual factors. First, many green innovations in the dataset are likely to be incremental or compliance-driven, rather than strategic or market-oriented. Such innovations may improve environmental outcomes but are less likely to translate into competitive advantages or revenue growth. Second, in the Portuguese context, limited access to green financing or insufficient scale of innovation activities may reduce the likelihood that such efforts lead to measurable financial returns. Lastly, it is possible that the benefits of these innovations – such as cost savings or enhanced brand value – take longer to materialize and are therefore not captured within the timeframe or financial indicators used in this analysis.

Therefore, it can be concluded that although one of the measures considered demonstrates some influence on firm profitability, the effect is not strong enough to unequivocally support the hypothesis being tested.

4. **Conclusion**

Understanding the link between environmental and financial performance in Portuguese firms offers valuable insights into how companies can pursue green strategies without compromising profitability. This study examined the relationships between green investment, green innovation, and financial performance in a sample of 6,849 firms from 2010 to 2021.

It was first noted that of the sample only 22.13% of firms made any environmental investment over the 12-year period, and that more than half of the firms (precisely, 56%) made only one green investment over the period. The econometric analysis yielded mixed results. While no statistically significant effect of green investment on financial performance was observed across the full sample, a more focused subsample of consistently surveyed firms revealed a positive and significant relationship. This suggests that sustained environmental investment may be more impactful than occasional efforts.

Regarding green innovation, the study found strong evidence that environmental innovations increase the likelihood of green investment. Among the six innovation indicators, EMAS certification, financial guarantees, and greenhouse gas reduction strategies were the most influential. This confirms that internal environmental capabilities and commitments shape firms' investment behavior.

However, when examining the impact of green innovation on financial performance, results were weak. Only the presence of a financial guarantee showed a minimal effect, with contradictory signs depending on the productivity measure used. This implies that green innovations, particularly those oriented toward compliance, may not immediately translate into improved profitability.

Future research should incorporate additional variables such as environmental regulatory costs, R&D intensity, participation in environmental partnerships or innovation networks, and perceptions of environmental risk. These may clarify the mechanisms through which environmental strategies influence firm performance.

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Appendix

Table A1 – Number of firms by industry, 2010–2021

NACE	Industry	Mean	S.D.	Min	Max
05–09	Mining and quarrying	53.5	4.93	45	63
10–12	Food products, beverages and tobacco products	274.92	21.43	245	313
13–14	Textiles and wearing apparel	211.25	21.41	172	242
15	Leather and leather products	86.00	9.31	72	100
16	Wood and wood products	67.25	7.36	55	77
17–18	Pulp, paper, paper products and publishing	123.67	8.42	111	144
19–21	Chemical and chemical products	117.5	8.02	107	136
22	Rubber and plastic products	98.33	10.39	83	124
23	Other non-metallic products	124.08	15.01	104	143
24	Basic metals	47.5	5.90	39	56
25	Fabricated metal products	164.67	23.62	130	212
26–27	Electronic and electrical equipment	93.17	11.44	74	111
29–30	Motor vehicles, trailers and other transport equip.	120.75	11.62	105	138
28–31–33	Other manufacturing industries	205.58	22.93	174	237
35–36	Electricity, gas and water	72.5	13.77	45	98

Source: Authors' calculations using STATA software.

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