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Bayes Business School (formerly Cass)
Faculty of Finance
106 Bunhill Row
London EC1Y 8TZ

The Role of Geopolitical and Climate Risk in Driving Uncertainty in European Electricity Markets

Peter Cincinelli, Elisabetta Pellini

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The role of geopolitical and climate risk in driving uncertainty in European electricity markets*

Peter Cincinelli† Elisabetta Pellini‡

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Abstract

This paper examines the occurrence of price bubbles in wholesale day-ahead electricity markets and investigates the impact of geopolitical and climate risk on such extreme price movements. The empirical analysis is executed for twelve major European electricity markets, namely APX (Netherlands), BPX (Belgium), EEX (Germany), EPX (United Kingdom), GME (Italy), NordPool (Finland, Norway and Sweden), OMEL (Portugal), OPCOM (Romania) and POWERNEXT (France). Our findings reveal that the probability of price bubbles increases with higher geopolitical risk and elevated air temperatures, while it decreases with greater precipitation and stronger wind speed. Specifically, a one-unit increase in geopolitical risk raises the probability of price explosiveness by 8.23%. These results underscore the urgent need for European countries to accelerate renewable energy deployment, enhance power system flexibility, and strengthen electricity market integration. Such measures are critical to achieving climate targets, protecting consumers from future energy crises, and supporting the affordable electrification of the manufacturing sector.

Keywords: Wholesale electricity market, Geopolitical risk, Climate risk, Energy transition, Price bubbles, Backward Supremum ADF.

J.E.L. Classification: C58, E30, Q41, Q47.

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† Department of Management, University of Bergamo (Italy).

‡ *Corresponding author.* Centre for Econometric Analysis and Faculty of Finance, Bayes Business School, City St George's, University of London (UK).

1 Introduction

In recent years, wholesale day-ahead electricity markets in Europe have experienced high prices and volatility, but unprecedented levels were reached between the Fall of 2021 and the end of Summer 2022, when prices went beyond 500 €/MWh, before collapsing in the first quarter of 2023 to 100 €/MWh. Notably, the wholesale day-ahead price of EEX-Germany rose from around 57 €/MWh in April 2021 to 187 €/MWh in December 2021, to 508 €/MWh in August 2022, and then dropped to around 99 €/MWh in March 2023. Similarly, the APX-Netherlands price went from around 58 €/MWh in April 2021 to 227 €/MWh in December 2021, to 497 €/MWh in August 2022, before collapsing to around 99 €/MWh in March 2023. The primary reason for the rise in electricity prices during 2021-2022 was the surge in natural gas price that resulted from Russia's decision to weaponise gas supply, which started before the invasion of Ukraine, and the fears of shortages that this move created. Since natural gas-fired power plants play a crucial role in covering electricity demand peaks, this led to an unprecedented increase in prices across all major European power exchanges.

The surge in wholesale electricity prices rapidly passed through to retail prices, resulting in a significant impact on the utility bills of all European consumers[1]. The events of 2021-2022 exacerbated energy poverty of households and led to the closure of many energy-intensive businesses. In European Union Member States, the statistics show that the energy poor and the low-income households were the most impacted by the energy crisis, because they spend significantly higher shares of their incomes on energy. Equally, rising energy prices had major repercussions on the production costs of the manufacturing sector, with a cascading effect on production, employment and prices (European Commission, 2021; Council of European Union, 2022). In Great Britain, the energy crisis also had a significant impact on consumers and energy suppliers, prompting the government to set a cap on electricity and gas bills well below the regulatory cap level (Pollitt et al., 2024).

European governments tried to mitigate the effects of the energy crisis by implementing temporary ad hoc measures such as income support for vulnerable consumers, reduced energy taxes, and caps on retail prices (Pollitt et al., 2024). In addition, a plan of actions, called REPowerEU, was set out in March 2022 to reduce dependence on Russian fossil fuels. The plan included measures to cut natural gas and electricity consumption, boost gas storage, increase fuel supply diversification, and accelerate the installation of new renewable capacity (European Commission, 2022). In March 2023, the European Commission proposed a comprehensive reform of the Union's electricity market, as a long-term strategy to better protect consumers from future energy crises, support investment in renewable generation and improve the flexibility of the system, which the energy transition makes more difficult to manage due to intermittency of renewable generation and increased electrification (European Commission, 2023). The proposed reform was then translated into the enactment of new legislation regarding the Union's electricity market design, namely Directive EU/2024/1711 (European Parliament and Council of the European Union, 2024a) and Regulation EU/2024/1747 (European Parliament and Council of the European Union, 2024b), which entered into force on the 16^{th} July 2024.

This study aims to determine if the remarkable electricity price increase of 2021-2022 can be classified as a price bubble, namely whether this was a significant deviation of price from its fundamental

[1] Retail prices showed a marked increase between the first half of 2021 and the second half of 2022. In the European Union, the average retail prices for household consumers went from 0.1341 €/kWh to 0.2401 €/kWh. The average retail prices for non-household consumers went from 0.0859 €/kWh to 0.1986 €/kWh. Source: Eurostat database: https://ec.europa.eu/eurostat/databrowser.

value. Despite the numerous insightful contributions on detecting price bubbles (also known as price explosiveness) in crude oil and natural gas markets, the empirical investigation of such episodes in electricity markets remains scarce. This paper fills this gap by identifying a novel characteristic of electricity prices, moving beyond the extensively studied features of volatility, spikes, and seasonality. Furthermore, there is a significant gap in the literature on the examination of factors behind the explosiveness of electricity prices. This paper aims to fill this gap by carrying out an empirical analysis that identifies periods of bubbles in European wholesale day-ahead electricity prices between 2006 and 2024 and unveils the impact of geopolitical and climate factors on the probability of bubble formation.

Our empirical analysis examines wholesale day-ahead electricity markets of twelve major European countries, each characterised by distinct energy mixes for electricity generation and levels of interconnection with neighbouring nations. These markets include APX (Netherlands), BPX (Belgium), EEX (Germany), EPX (United Kingdom), GME (Italy), NordPool (covering Finland, Norway, and Sweden), OMEL (Spain), OMEL (Portugal), OPCOM (Romania), and POWERNEXT (France). The empirical strategy consists of two steps. First, we investigate the presence of periods of explosiveness in wholesale day-ahead electricity prices, by using the Backward Supremum Augmented Dickey-Fuller (BSADF) test of Phillips et al. (2015a, 2015b). Specifically, we follow the approach of Phillips & Shi (2020) which allows to identify multiple bubble episodes with a bootstrap procedure that mitigates the potential impact of both heteroscedasticity and multiplicity issues in recursive testing[2]. Second, we evaluate how bubbles in wholesale day-ahead electricity prices are sensitive to geopolitical risk, climate, and economic indicators by estimating a panel probit model. We also conduct an in-sample forecasting exercise.

Our findings can be summarised as follows. First, we find a prolonged period of explosiveness in European wholesale day-ahead electricity prices starting from October, 27^{th} 2021. This phase began when President Putin ordered Gazprom to fill European gas storage only after securing Russia's own reserves needs. Second, from February, 24^{th} 2022, the day Russia invaded Ukraine, electricity prices entered a new phase of explosiveness. The conflict and the resulting geopolitical tensions led to a sharp increase in natural gas prices on European gas exchanges, which was caused not only by a tight demand-supply balance, but also by the expectations of further supply cuts, which made buyers price-insensitive. This quickly impacted wholesale electricity prices because natural gas-fired power plants are often the price-setting technology in the wholesale day-ahead electricity market. However, also extreme weather conditions in both the summers of 2021 and 2022 may have played a role in the formation of the electricity price bubbles, as they determined reduced renewables and nuclear production which in turn resulted in a higher use of natural gas-fired power plants for electricity generation, which further increased wholesale day-ahead electricity prices. Our analysis indicates that certain countries, such as the Netherlands and Italy, experienced prolonged periods of price explosiveness lasting 44 and 50 weeks, respectively, whereas Sweden only showed a 9-week duration. Since the end of Summer 2022, due to the implementation at a record time of several measures to strengthen the security of gas supply and reduce gas and electricity consumption, prices went on a steep downward pathway, and no further periods of explosiveness occurred.

[2]The test was originally proposed to detect bubble periods in stock prices, exchange rates and other financial time series (Phillips et al., 2015a; Phillips & Shi, 2018, 2019), and has then been adopted to test for bubbles in commodity markets in several studies (see among others Caspi et al. (2018), Sharma & Escobari (2018), Figuerola-Ferretti et al. (2020), Khan et al. (2021, 2022), Akcora & Kocaaslan (2023), Wang et al. (2024)).

After identifying episodes of price bubbles, we quantify their sensitivity to geopolitical, climate and economic indicators, by estimating a panel probit model. The results show that the probability of experiencing price explosiveness increases with higher levels of geopolitical risk and air temperature, while it decreases with higher precipitation levels and stronger wind speed. In particular, we find that an increase of one unit in geopolitical risk increases the probability of a bubble by 8.23%, as geopolitical instability disrupts the current supply of fossil fuels and creates fears of future shortages. A 1-degree Kelvin increase in air temperature increases the probability of a bubble by 0.15%, which is mainly due to higher electricity demand for cooling. Conversely, a 1-unit increase in wind speed reduces the bubble probability by 2.28%, as stronger wind speed allows producing electricity from wind turbines rather than by using fossil fuel plants, with the effect of lowering prices. Finally, the in-sample forecasting exercise shows the high degree of accuracy of the panel probit model in predicting the occurrence of price bubbles. To the best of our knowledge, this is the first study that examines the issue of explosiveness in European wholesale day-ahead electricity markets and attempts to understand the underlying drivers.

The remainder of the paper is organised as follows. Section 2 presents a review of studies and outlines the research hypotheses. Section 3 describes the data, the econometric methodology, and the empirical findings, including an in-sample forecasting exercise. Section 4 concludes.

2 Literature review and hypotheses development

Several studies have been conducted over the past years to identify periods of bubbles in energy prices, predominately for crude oil, oil derivatives, natural gas and coal. Caspi et al. (2018) detect periods of oil price explosivity in the US between 1876 and 2014 and find that financial crises are followed by energy price bubbles. This result is confirmed by Sharma & Escobari (2018) and by Khan et al. (2022) who test for the existence of bubbles not only in crude oil price, but also in oil products prices (i.e. heating oil and jet fuel) and natural gas price. Figuerola-Ferretti et al. (2020) provide an analysis of benchmark crude oil prices Brent and West Texas Intermediate and find explosivity prior to the peak of the global financial crisis of 2008 and price decline in 2014-2016, which started after a key OPEC meeting in November 2014. Li et al. (2022) verify the existence of bubbles for steam coal price in China. Akcora & Kocaaslan (2023) focus on several European natural gas markets and demonstrate that more mature gas exchanges are subject to fewer bubbles. They also show that the timings of the bubbles are quite similar across markets, indicating therefore a substantial degree of market integration in European natural gas markets. Zhang et al. (2018) show that Japan and European natural gas prices have more bubbles than US prices and attribute this to the different pricing mechanism existing in these countries.

Global economic activity, geopolitical risk and climate conditions have been indicated as important drivers for bubbles in energy prices. Li et al. (2020) examine bubbles in natural gas prices of Europe, US and Asia and identify different causes for bubbles formation in the three markets, namely geopolitical factors in Europe, economic euphoria and oil price fluctuation in Asia, and speculation in the US. Khan et al. (2021) detect multiple bubbles in the global price of coal and find as the main driver economic growth. Su et al. (2023) investigate bubbles in the price of natural gas in Europe and identify as the main determinants both geopolitical risk and climate factors. Wang et al. (2024) identify as main driver of coal price bubbles in China volatility in alternative energy sources, energy policies, extreme weather conditions, and the macroeconomic environment. The conflict between Russia and Ukraine was one of the main determinants of bubbles in crude oil futures, as found by Chang (2024).

The detection of bubbles in electricity prices has received limited attention in the literature, the exceptions being Gupta & Inglesi-Lotz (2016) and Doran et al. (2025). Gupta & Inglesi-Lotz (2016) investigate the existence of bubbles in the electricity prices in South Africa from 1965 to 2013. They detect two episodes of price bubbles: the first occurring between 1971 and 1998, which they link to the unregulated monopolistic structure of the country's electricity market during that period, and the second happening in 2008–2009, caused by a significant supply crisis. However, Gupta & Inglesi-Lotz (2016) do not quantify the impact of drivers on the probability of bubble formation. In a recent paper, Doran et al. (2025) test for bubbles in retail electricity prices for household consumers in Romania and Germany over the period 2007-2022 and identify two bubbles for each market. For both countries the second bubble occurred after the outbreak of the war between Ukraine and Russia, while the first bubble coincided with the 2008 financial crisis for Germany and with the elimination of regulated tariffs for domestic consumers in 2012 for Romania. However, neither Doran et al. (2025) quantify the impact drivers on the probability of bubble formation. To the best of our knowledge, no other study has focused on the detection of bubbles in liberalised competitive electricity markets.

One of the reasons for this lack of studies could be that up until recently, electricity was a vertically integrated business in most of the countries around the world, with state-owned monopolists controlling the entire supply chain. As pointed out by Weron (2006), while Chile pioneered power market liberalisation in 1982, it was not until the mid-1990s that other nations began to adopt similar reforms (among the first countries were England and Wales, Australia, northeastern US states of Pennsylvania, New Jersey and Maryland, and California). The European Union enacted the first directive to liberalise the electricity industry with the aim of creating a single EU-wide market in 1996 (Bosco et al., 2010). Currently, competitive markets determine the price of electricity in many countries around the world, and spikes and seasonality[3] have been the two most studied characteristics of wholesale day-ahead electricity prices (see among others Knittel & Roberts (2005), Koopman et al. (2007), Escribano et al. (2011)). Our paper therefore aims to fill this gap in the literature on characteristics of electricity prices, by conducting a comprehensive study of bubbles in wholesale electricity markets across twelve major European countries and by assessing the contribution of three major potential drivers to the probability of bubble formation.

The following sections discuss the potential effects on electricity price bubbles of geopolitical risk (*Section 2.1*), climate (*Section 2.2*), and economic indicators (*Section 2.3*) and formulate the research hypotheses.

2.1 Geopolitical risk indicators

Li et al. (2020), Su et al. (2023) and Chang (2024) argue that geopolitical factors play a significant role in the formation of bubbles in energy prices. This has been particularly evident with the Russian invasion of Ukraine, which highlighted the risk of dependence of G7 countries, particularly Europe, on

[3] On the one hand, due to the impossibility of storing electricity, sudden and unexpected power plant outages and spikes in demand resulting from heatwaves may result in huge, but short-lived, price increases. On the other hand, seasonality in electricity demand, driven by seasonality in temperature and daylight hours, determines the seasonality in electricity prices.

Russia's fossil fuels and routes, as pointed out by Balsalobre-Lorente et al. (2023) and Emiliozzi et al. (2024). Currently, the level of geopolitical risk is elevated due to the ongoing conflicts in Ukraine and the Middle East. This is further exacerbated by the uncertainty that stems from the impending political elections in the United States.

To evaluate the impact of geopolitical tensions on the formation of price bubbles for European wholesale day-ahead electricity prices, we use the geopolitical risk index developed by Caldara & Iacoviello (2022). The index is based on automated text searches of the electronic archives of major Western newspapers and it is computed by counting the monthly number of articles related to adverse geopolitical events in each newspaper, expressed as a proportion of the total number of news articles. The choice of the Caldara & Iacoviello (2022) geopolitical risk index over other indexes, despite potential media bias, is due to its provision of country-specific indexes for 44 countries with monthly and daily frequency. Another advantage of Caldara & Iacoviello (2022) stems from the inclusion of various sources of geopolitical risk, namely war threats, peace threats, military build-ups, nuclear threats, terrorism threats, and the onset and escalation of conflict. Among the possible alternative indexes not based on media coverage, there exists the PRS Group International Country Risk Guide[4] which, however, covers a broader range of risks than the sole geopolitical ones, including political, economic and financial risks. By contrast, the Global Terrorism Database[5] only focuses on terrorism acts and its project ended in 2020. The Uppsala Conflict Data Program (UCDP)[6] tracks actual violent events, but not perceived risks, which are equally important for generating bubbles in energy prices. Additionally, the UCDP data is available only at an annual or periodic frequency.

The first hypothesis can therefore be expressed as ***H1*:** *geopolitical risk disrupts or generates expectations of disruptions of natural gas supply, causing natural gas prices to increase, and consequently leading to electricity price bubbles.*

2.2 Climate indicators

Previous studies have shown that in competitive wholesale day-ahead electricity markets, prices are sensitive to climate indicators such as temperature, wind speed, and precipitation. As pointed out by Mosquera-López et al. (2017), weather is an important driver of electricity prices because renewable technologies (i.e. solar and wind technologies) are weather sensitive and so is electricity demand. As discussed in Gianfreda et al. (2023) the increasing penetration of renewable power plants due to the decarbonisation targets has added complexity to the market, because these technologies can produce in an intermittent and unpredictable way according to weather conditions. Mosquera-López et al. (2018) show how freezing temperatures reduce hydropower generation and increase electricity prices in the Nordic countries. Mosquera-López et al. (2024) demonstrate that wind impacts electricity prices in a nonlinear manner. Thus, if there is enough precipitation, wind and sun, electricity demand can be satisfied by renewables and nuclear plants in most of the hours of the day, and electricity prices are low. Otherwise, fossil fuel power plants must be scheduled to cover demand.

To evaluate the impact of climate variables on the formation of bubbles in European wholesale day-ahead electricity prices, we consider three indicators: [i] air temperature; [ii] precipitation; and [iii]

[4]PRS Group International Country Risk Guide available at `https://www.prsgroup.com/explore-our-products/icrg/`

[5]Global Terrorism Database (GTD), available at `https://www.start.umd.edu/data-tools/GTD`

[6]Uppsala Conflict Data Program, available at `https://ucdp.uu.se/encyclopedia`

wind speed.

The second hypothesis can therefore be split into: ***H2a*: *higher air temperature leads to an increased demand of electricity for cooling, which makes natural gas-fired power plants the electricity price setting technology more often than usual, leading to the formation of price bubbles.* ***H2b*: *a decrease in precipitation lowers hydroelectric and nuclear power production, determines a greater use of natural gas-fired power plants, and hence increases the probability of price bubbles; for the same reason, reduced wind speed decreases wind power generation, thereby raising the risk of price bubbles.*

2.3 Economic indicators

As argued by Khan et al. (2022) strong economic growth and rapid decline are associated with bubbles in energy prices. Large changes in industrial production can drive up fossil fuel prices used in electricity generation, increasing costs, and contributing to electricity price bubbles.

To evaluate the impact of economic activity on the formation of bubbles for European wholesale day-ahead electricity prices, we consider the monthly change in the industrial production index. The third hypothesis is therefore: ***H3*: *higher industrial activity changes generate an increased demand for fossil fuels, which may lead to a surge in their prices with the consequence of electricity price bubbles.*

3 Methodology and empirical analysis

In this paper, we consider the following time series of wholesale day-ahead electricity prices for the period January 2006-May 2024: APX (Netherlands), BPX (Belgium), EEX (Germany), EPX (United Kingdom), GME (Italy), NordPool (Finland, Norway and Sweden), OMEL (Spain), OMEL (Portugal), OPCOM (Romania) and POWERNEXT (France) (source: Refinitiv).

Figure 1 shows the time series of wholesale day-ahead electricity prices for the European countries considered[7]. From the plots, it emerges that electricity prices started to increase after mid-2021, and well before the invasion of Ukraine from Russia. Among the reasons for this behaviour are the post-pandemic economic recovery which generated a surge in natural gas demand, the decision of Russia to scale back short-term natural gas sales and not refill storage in Europe; and the influence of weather-related events on electricity demand and generation.

[INSERT SOMEWHERE HERE FIGURE 1]

3.1 Testing for bubbles

Over the past four decades, economists have extensively debated the mechanisms that can lead to price bubble formation, in particular on whether bubbles are rational or behavioral. Rational bubble models are the oldest and most developed type of model for explaining bubbles in asset prices and generally build on the present-value model of asset prices. Specifically, these models assert that in the presence of bubbles, asset prices are driven by two components, one being the economic fundamentals and a second one, the bubble, which explains the deviation of the observable asset prices from the fundamentals (Blanchard, 1979; Stiglitz, 1990).

[7] In the Internet Appendix A, we report the time series of electricity prices for each country separately.

Several econometric methods have been proposed to detect and date-stamp bubbles in asset prices (see Wöckl (2019) and Gürkaynak (2008) for a review of empirical research on price bubbles). Early research in the 1980s and 1990s on econometric methods for detecting bubbles in asset prices included variance bounds tests (see among others Blanchard & Watson (1982)), West's two-step tests (West, 1987), and standard unit root and cointegration tests (see among others Campbell & Shiller (1987), Diba & Grossman (1988), Froot & Obstfeld (1991)).

Evans (1991) criticises using standard unit root and cointegration tests for bubbles detection, by demonstrating with simulated data that they cannot distinguish stationary processes from periodically collapsing bubbles. Right-tailed recursive unit root tests have been developed in the last two decades (see among others Phillips et al. (2011, 2015a, 2015b)) to address the criticism pointed out by Evans (1991). In particular, the Backward Supremum Augmented Dickey Fuller (BSADF) test of Phillips et al. (2015a; 2015b, hereafter PSY) has been shown to outperform previous econometric tests in detecting multiple bubble episodes and to correctly date-stamp historical episodes of financial bubbles in the S&P 500 stock market, over the period from January 1871 to December 2010. The BSADF testing procedure also offers an ex-ante real-time dating strategy that can give an early warning diagnostic for price bubbles. This is particularly relevant from a market surveillance point of view, as it can be used to alert market participants, regulators, and governments of the onset of a period of price explosiveness. Finally, the BSADF test is an empirical approach that is compatible with various theoretical explanations of bubble-generating mechanisms in the literature of rational bubbles, such as rational bubble models with symmetric information (Blanchard, 1979), intrinsic bubbles (Froot & Obstfeld, 1991), and herd behaviour. For all of the above reasons, in this paper, we implement the BSADF testing procedure to detect and date-stamp bubbles in electricity markets. In particular, we follow the approach proposed by Phillips & Shi (2020) which implements a bootstrap procedure that simultaneously addresses both heteroscedasticity and multiplicity issues in testing. This procedure has been shown to outperform the forward recursive algorithm (Phillips et al., 2011), the rolling window approach (Shi, 2017), and the CUSUM monitoring strategy (Homm & Breitung, 2012).

The empirical regression model to detect bubbles in the time series of weekly electricity prices is the following ADF regression:

$$\Delta y_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} y_{t-1} + \sum_{i=1}^{k} \delta^i_{r_1,r_2} \Delta y_{t-i} + \varepsilon_t \tag{1}$$

where Δ is the first-difference operator; y_t is the time series of interest at time t; k is a scalar that denotes the number of lags of the dependent variable that are included to accommodate serial correlation; r_1 and r_2 are the fraction of the total number of periods in the sample that specify the starting and the ending points, respectively; α_{r_1,r_2}, β_{r_1,r_2} and $\delta^i_{r_1,r_2}$ are regression coefficients; ε_t is the error term.

The null hypothesis of a unit root in y_t is $H_0 : \beta_{r_1,r_2} = 0$, while the alternative of bubble is $H_1 : \beta_{r_1,r_2} > 0$. The ADF test statistic corresponding to the null hypothesis is given by: $ADF_{r_1}^{r_2} = \frac{\hat{\beta}_{r_1,r_2}}{SE(\hat{\beta}_{r_1,r_2})}$.

To detect a single bubble episode, Equation (1) is estimated using a forward expanding sample (Phillips et al., 2011). The starting point of the sub-sample is held constant at $r_1 = 0$, while the end of the sub-sample, r_2, increases from r_0 (the minimum window size) to 1 (the entire sample period).

Equation (1) is recursively estimated and yields a sequence of $ADF_0^{r_2}$ statistics. The supremum of the sequence represents the SADF and is defined as follows:

$$SADF_{r_0} = \sup_{r_2 \in [r_0,1]} ADF_0^{r_2} \tag{2}$$

When the SADF statistic exceeds the right-tailed critical value, the unit root hypothesis is rejected, and the bubble period is accepted. However, a limit of this procedure is that it reliably estimates the starting and ending dates of the initial bubble, but it may not accurately capture the dates for subsequent bubbles.

To overcome this limitation, Phillips et al. (2015a,b) propose the Generalized SADF (GSADF), an extension of the SADF, which has the same alternative hypothesis as the SADF, but covers a larger number of sub-samples. The GSADF test involves an extensive set of regressions, where the first observation varies from 0 to $r_2 - r_0$, while the last varies from r_0 to 1. The GSADF, compared to the SADF test, has greater flexibility in the estimation window and allows to identify multiple periods of bubble. The GSADF statistic is defined as:

$$GSADF_{r_0} = \sup_{r_2 \in [r_0,1], r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2} \tag{3}$$

If test statistic exceeds the right-tailed critical value, the unit root hypothesis is rejected in favour of multiple periods of bubbles. Therefore, the SADF and the GSADF methodologies can provide a sequence of episodes of bubbles. The identification of bubbles is based on the time series characteristics of the prices series. During the expansion phase of a bubble, prices exhibit a mildly explosive behavior. Conversely, in times of crises, price movements often shift to a random drift martingale, usually coupled with a series of negative shocks. The PSY test, by providing a joint test for the drift and the autoregressive coefficients of the ADF model, allows detecting both bubbles and crises.

As a date-stamping strategy, Phillips et al. (2015a,b) propose to perform a double recursive test procedure, named BSADF statistic, which is defined as follows:

$$BSADF_{r2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \left\{ BADF_{r_1}^{r_2} \right\} \tag{4}$$

where r_1 and r_2 are the beginning and the ending fraction of the sample, with $r_1 < r_2$; r_0 is the fractional threshold and it is chosen on a lower bound of 1% of the full sample according to: $r_0 = (0.01 + 1.8/\sqrt{T})$, where T is the number of observations; r_w is the window size of the regression, as $r_1 - r_2$. Following Phillips & Shi (2020), we apply the BSADF test using the bootstrap procedure to mitigate the potential influence of unconditional heteroscedasticity and to address the multiplicity issue in recursive testing. Internet Appendix B describes both estimation methods.

We provide a set of figures which display the sequence of BSADF statistics (blue line) and shaded areas representing periods of bubbles. These periods are identified when the BSADF statistics exceed the 95% bootstrapped critical value, with number of bootstraps=499[8].

[8] The finite sample critical values for 90%, 95% and 99% confidence levels are obtained from Monte Carlo simulations with 2,000 replications (see Phillips et al. (2015a,b) and Vasilopoulos et al. (2022)). The window size is given by $r_0 = \left(0.01 + 1.8/\sqrt{T}\right)$ as recommended by Phillips et al. (2015a,b), and each time series has a different number of observations.

[INSERT SOMEWHERE HERE FIGURES 2-13]

Table 1 reports the descriptive statics for wholesale day-ahead electricity prices and BSADF statistics. In addition, Table 2 reports the periods of bubbles (in the number of weeks) for electricity prices. The Netherlands and Italy show longer periods of bubbles, with 44 and 50 weeks, respectively, while Sweden and Finland exhibit only 9 and 14 weeks, respectively. The difference in bubble duration across countries can be attributed to several factors that vary between countries, most notably the energy mix. Italy and the Netherlands generate 45% and 38% of their electricity from natural gas, respectively[9]. In contrast, hydro is the most important source of electricity, accounting for 40% of the generation in Sweden, while in Finland, nuclear accounts for 42% of the generation[10]. Other country-specific factors that play a role in the difference in bubble duration across countries include the adequacy of the transmission grid to host renewable generation capacity and meet demand in distant locations, the presence of bottlenecks on the grid leading to congestion, the degree of interconnection with neighbouring countries that allows electricity flows across countries, and the degree of competition in wholesale electricity markets.

[INSERT SOMEWHERE HERE TABLES 1 & 2]

Table 3 presents a timeline of key events related to the energy crisis, along with the corresponding periods of bubbles for electricity prices[11]. First, we find a prolonged period of price explosiveness in European wholesale day-ahead electricity markets starting from October, 27^{th} 2021. This phase coincided with when President Putin ordered Gazprom to fill European gas storage only after securing Russia's own reserves needs. Second, from February, 24^{th} 2022, the day Russia invaded Ukraine, electricity prices entered a new phase of explosiveness which lasted till the end of Summer 2022. The weaponisation of natural gas supply by Russia with the decision to cut the flow from Nord Stream 1 pipeline led to a sharp increase in natural gas prices for European consumers, which quickly impacted electricity prices. Natural gas is in fact a primary input in electricity generation, and natural gas-fired power plants play the role of the marginal plant in several hours of the day, typically when demand is at its highest or when other technologies, such as renewables or nuclear are not available[12]. Zakeri et al. (2023) estimate that natural gas-fired power plants set electricity prices for more than 80% of the hours in 2021 in Belgium, Great Britain, Greece, Italy, and the Netherlands. Tertre (2023) argues that while the tight natural gas supply-demand balance explain most of the price increase in 2021-2022, the extremely high natural gas prices in the Summer 2022 were the result of fears of further supply disruptions by Russia (that did not occur) coupled with the fact that some market operators became

[9] `https://www.iea.org/countries/the-netherlands/electricity` and `https://www.iea.org/countries/italy/electricity`

[10] `https://www.iea.org/countries/sweden/electricity` and `https://www.iea.org/countries/finland/electricity`

[11] In the Internet Appendix C, we report a comprehensive list of all events related to the energy crisis.

[12] The wholesale day-ahead market is run through a series of auctions in which the electricity market operator receives and processes bids for electricity sales and purchases for each hour of the following day. Producers' bids are ordered ascendingly according to their marginal costs of production, i.e., fuel and CO2 costs, to form a supply curve known as the merit-order curve. Equally, bids on the demand side are ordered descendingly. From such ordering a demand curve derives. The point where the demand meets the supply curve represents the equilibrium price, which corresponds to the marginal cost of the system, i.e. the marginal cost of production of the most expensive generating unit that is needed to satisfy the demand (the so-called marginal plant). The equilibrium price is then equally paid to each power plant, irrespective of their bids. `https://energy.ec.europa.eu/topics/markets-and-consumers/electricity-market-design`

price-insensitive buyers for security of supply reasons. In addition to the crisis in the natural gas market, extreme weather conditions in both the summers of 2021 and 2022 also played a role in the formation of the electricity price bubbles. Summer 2021 recorded lower than usual water and wind availability, resulting in reduced renewable energy production. Summer of 2022 experienced a prolonged drought, causing a shortfall in electricity production from nuclear power plants across various European countries due to insufficient cooling water availability, alongside a decrease in hydropower generation. In addition, low water levels in major rivers of continental Europe adversely affected the transport of coal used as input fuel for electricity generation. The reduced availability of hydro, nuclear and coal-fired power plants resulted in a higher use of natural gas-fired power plants for electricity generation, which further increased wholesale electricity prices.

[INSERT SOMEWHERE HERE TABLE 3]

3.2 Understanding the drivers of electricity prices bubbles

To understand the contribution of geopolitical risk, climate and economic indicators in driving bubble episodes in wholesale day-ahead electricity prices, we consider the following variables: [i] *Geopolitical Risk* by Caldara & Iacoviello (2022), which is defined as "*the threat, realisation, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations*" (p. 1195); [ii] *Air Temperature* which is the ambient air temperature measured at the height of 2 metres above the ground in Kelvin degrees (source: Copernicus); [iii] *Precipitation* which is the amount of rain, snow, sleet, or hail in metres that falls over a specific period of time in a particular area (source: Copernicus); [iv] *Wind Speed* which is the wind speed in metres per second measured at the top of a 10 metres tower using an anemometer (source: Copernicus); and [v] Δ*Industrial Production* which is the monthly change in the industrial production index (source: Eurostat for European countries, Office for National Statistics for United Kingdom)[13].

Table 4 reports some descriptive statistics of the monthly drivers of electricity price bubbles. The UK, France and Germany show the highest mean geopolitical risk, with values of 0.99, 0.53 and 0.44, respectively. This reflects the several adverse events that have affected these countries in recent years. Portugal has the lowest mean geopolitical risk (0.02), indicating how this country enjoys a much safer environment than major European countries. Geopolitical risk is not available for Romania. Air temperature varies significantly across countries, with Portugal having the highest mean temperature (288.48 K), followed by Spain with a value of 287.36 K, while Norway displays the lowest mean temperature (275.66 K) among the countries. The situation is the opposite when it comes to precipitation level, with Norway exhibiting the highest mean precipitation value (0.11 m), and Spain the lowest (0.05 m). The UK and the Netherlands have the highest mean wind speed (4.32 m/s and 4.24 m/s, respectively), while Italy has the lowest mean wind speed (2.04 m/s). The average change in industrial production is close to zero for most of the countries, with Romania showing the largest mean change (0.16) among all the countries considered.

[INSERT SOMEWHERE HERE TABLE 4]

[13] The explanatory variables are stationary. The complete results of the Im et al. (2003) and Pesaran (2007) panel unit root tests are not included here but are available upon request.

To quantify the contribution of each of these variables in predicting electricity price bubbles, we employ a panel probit model with random effects at monthly frequency[14]:

$$Pr(Price_{i,t} \neq 0 | x_{k,i,t-j}) = \Phi(x_{k,i,t-j}\beta + \nu_i) \tag{5}$$

where: $Price_{i,t}$ is a binary variable for electricity price bubbles in country i at time t. The variable takes the value 1 if the BSADF test indicates that price in country i is in a bubble state in at least one of the weeks of a given month, and 0 otherwise; Φ is the cumulative normal distribution function; ν_i are i.i.d., $N(0, \sigma_\nu^2)$. This model is based on the variance components framework: $y_{i,t} \neq 0 \Leftrightarrow x_{k,i,t}\beta + \nu_i + \varepsilon_{i,t} > 0$, where $\varepsilon_{i,t}$ are i.i.d. Gaussian distributed with mean zero and variance $\sigma_\varepsilon^2 = 1$, independently of ν_i. $x_{k,,t-j}$ is a vector of k potential bubble drivers in country i at time $t-j$ with $j = 0, ..., 2$.

We estimate alternative specifications for this model, each with a different number of lags of the predictors, to account for lagged effects of the predictors on the probability of a price bubble. We select the best fitting model adopting the Bayesian Schwartz information criterion (BIC).

Table 5 reports the results of the final selected model Equation (5). Column [i] reports the estimated coefficients for the full sample, column [ii] reports the estimated average marginal effects, which tell us the effect of a one-unit increase in a given predictor on the probability of having a bubble, and column [iii] shows the Variance Inflation Factors (VIFs) to check for multicollinearity.

Our findings indicate that electricity price bubbles are highly sensitive to both geopolitical risk and climate indicators. The probability of experiencing a price bubble increases with higher geopolitical risk and air temperature, while it decreases with higher precipitation level and stronger wind speed. The results provide support for *H1*, *H2a* and *H2b*. Specifically, by computing the average marginal effects, we can see that a one-unit increase in geopolitical risk increases the probability of an episode of price explosiveness by 8.23%. Geopolitical instabilities disrupt the natural gas supply chain and create fears of future shortages, leading to higher natural gas prices, which, in turn, determine episodes of electricity price bubbles. A one-degree Kelvin increase in air temperature raises the probability of a bubble by 0.15%. Hot weather typically results in increased electricity demand for cooling purposes. This can lead to consumption peaks that require immediate switch-on of natural gas-fired plants and cause the emergence of price bubbles. In contrast, a one-unit increase in wind speed reduces the probability of a price bubble by 2.28%. Higher wind speed determines a greater production of electricity from wind turbines and less use of fossil fuel plants, reducing the chances of electricity price bubbles. Higher levels of precipitation also reduce the chances of electricity price explosiveness, although this result is marginally statistically significant. *H3* is not supported by the results, as changes in industrial production do not appear to have a statistically significant impact on the probability of experiencing price bubbles. Finally, column [iii] of Table 5 shows that multicollinearity is not a concern, given that the maximum VIF is 1.25, which is far below the generally employed cut-off of 10, and the average value of the model is not considerably larger than 1 (Chatterjee & Hadi, 2015).

The econometric methodology and the empirical findings in this paper advance the understanding of the dynamics of European electricity markets and, more generally, of competitive and liberalised electricity markets. By finding that electricity prices, like other energy commodity prices, are subject

[14]The use of monthly frequency is dictated by the availability at monthly frequency of the industrial production index and of the climate indicators.

to bubbles, this study highlights the limitations of the previous electricity market design of European countries in protecting consumers and suppliers from explosiveness in wholesale price of electricity, as indicated by Fabra (2023) and Pollitt et al. (2024). In particular, our findings that bubbles are likely to be driven by geopolitical and climate factors stress the importance of having a market design that prioritises the security of energy supply, while achieving the decarbonisation targets. A secure energy supply requires not only diversification of fossil fuel imports, but also the availability of enough firm capacity (i.e. that provided by thermal and nuclear power plants), within-country transmission capacity at the location where renewable plants are, and interconnection capacity for cross-border trade of electricity to facilitate the use of renewable resources, until energy storage solutions are fully operational. Lastly, the deployment of demand response tools and dynamic price contracts is another fundamental element to allow consumers using electricity when it is cheapest, for example when it is produced via renewable plants, and to reduce consumptions peaks. In other words, our empirical findings confirm the need for a swift implementation of the European Parliament and Council of the European Union (2024a, 2024b), also known as the EU Electricity Market Reform (EMR), which sets out new rules for the Union's electricity market design. The key pillars of the EMR are: the promotion of long-term contracts between generators and customers, including large energy users, suppliers, and governments to provide more stable prices for customers and more secure revenues for generators with the aim of pushing investment in low-carbon power plants; the requirement for suppliers to offer fixed-term, fixed-price electricity supply contracts to better protect consumers and dynamic electricity price contracts to allow gaining the most from renewable generation; the right to energy sharing, which allows final customers (e.g. households, small and medium-sized enterprises) to share the electricity they produce between themselves; the access to affordable energy during an electricity price crisis, which can be called by the Council when certain conditions of high prices are met; a better protection for vulnerable customers from electricity disconnections and more generally for all customers via the appointment of a supplier of last resort that takes over the supply of electricity to customers of a supplier which has ceased to operate. The timely implementation by Member States of the measures indicated in the EMR will be critical to achieving the Union's objectives of a clean, secure and affordable energy for all its citizens.

[INSERT SOMEWHERE HERE TABLE 5]

3.3 In-sample forecasts

In this section, we perform an in-sample forecasting exercise to compute the probability of a bubble in electricity prices. Figure 14 presents in-sample forecasts of price bubbles for each electricity market over the time period 2007:2-2024:4, with the exception of Romania for which predictions could not be made due to unavailability of geopolitical risk variable. Each plot shows the predicted probabilities of experiencing bubble episodes based on the underlying panel probit model. The shaded areas show the periods of bubbles in electricity prices as identified by BADF tests conducted in Section 3.1.

The results reveal that the panel probit model is able to predict the occurrence of bubbles correctly for most of the electricity markets, for almost all periods in which bubbles have been identified by the BADF tests. In particular, the panel probit model shows very high accuracy in predicting bubbles for the EPX price. For this market, the model predicts the occurrence of the March 2022 bubble with 80% probability. For the EEX price and the Powernext price, the model predicts the occurrence of the bubble of March 2022 with 43% and 35% probability, respectively. The forecast accuracy of the model is also confirmed for all periods when bubbles did not occur. Finally, the level of accuracy in identifying price bubbles is also evaluated in the analysis of optimal cut points reported in the Internet Appendix D.

[INSERT SOMEWHERE HERE FIGURE 14]

4 Conclusions and policy recommendations

This paper examined the occurrence of bubbles in wholesale day-ahead electricity prices and identified their drivers for twelve major power markets in Europe, namely APX (Netherlands), BPX (Belgium), EEX (Germany), EPX (United Kingdom), GME (Italy), NordPool (Finland, Norway and Sweden), OMEL (Spain), OMEL (Portugal), OPCOM (Romania) and POWERNEXT (France). For bubble detection, we used the Backward Supremum Augmented Dickey-Fuller (BSADF) test of Phillips et al. (2015a, 2015b). Specifically, we followed the approach of Phillips & Shi (2020) which allows to identify multiple bubble episodes with a bootstrap procedure that mitigates the potential impact of both heteroscedasticity and multiplicity issues in recursive testing.

Our findings indicate that there were two distinct periods of price bubbles in European wholesale day-ahead electricity prices. The first bubble began on October 27^{th}, 2021, coinciding with President Putin's directive for Gazprom to prioritise filling Russia's gas reserves before European storages. The second bubble emerged from February 24^{th}, 2022, the day Russia invaded Ukraine. The ensuing conflict and geopolitical tensions caused significant disruptions in the natural gas supply chain and generated fears of scarcity even beyond actual shortages, resulting in extremely high natural gas prices, which in turn led to electricity price bubbles. Adverse weather conditions led to a decreased availability of renewable and nuclear power plants, which also played a role in the emergence of electricity price bubbles during both periods.

After identifying episodes of price bubbles, we estimated a panel probit model to assess the sensitivity of price bubbles to geopolitical risk, climate and economic indicators. The results show that the probability of experiencing price bubbles increases with higher levels of geopolitical risk and air temperature, while it decreases with higher precipitation levels and stronger wind speed. In particular, we find that a 1-unit increase in geopolitical risk raises the bubble probability by 8.23%. Geopolitical instabilities disrupt the natural gas supply chain and create fears of future shortages, leading to higher natural gas prices, which, in turn, determine episodes of electricity price bubbles. A 1-degree Kelvin increase in air temperature increases the probability of a bubble by 0.15%, which is mainly due to higher electricity demand for cooling. Conversely, a 1-unit increase in wind speed reduces the bubble probability by 2.28%, as stronger wind speed allows producing electricity from wind turbines rather than by using fossil fuel plants, with the effect of lowering prices. Finally, we conducted an in-sample forecasting exercise to test the accuracy of the panel probit model in predicting the occurrence of price bubbles.

The empirical results of this study offer several policy insights for European countries and, more generally, for all countries that are fossil-fuel dependent aiming to transition to a low-carbon economy, while protecting consumers from future price bubbles. Policy makers can achieve these goals by implementing measures that address both the demand and the supply sides of the market. From the demand side, the enactment of policies aimed at enhancing energy efficiency in buildings through better insulation, and encouraging the replacement of outdated appliances with newer, more efficient models, would play a crucial role in curbing electricity demand. This also requires adequate financial support mechanism, and financing options that allow to reduce the risk of energy efficiency private investments. The European Union has taken important steps in this direction, by enacting several legislative acts, all guided by the so-called *Energy Efficiency First* principle. Other countries could follow its example. The complete rollout of demand-side management tools, such as smart meters, smart grids and dynamic price contracts, will also be pivotal to empower consumers and reduce electricity bills. Smart meters, by providing data on electricity usage and price in real time, give consumers control over their electricity use and also allow them to consume electricity when it is cheapest, therefore smoothing out peaks of load, which are those necessitating the use of natural gas-fired power stations. Smart grids instead allow individual consumers and communities who produce their own renewable energy to sell it back to the grid or to share it among themselves, making them energy prosumers.

From the supply side, policy makers need to ensure that the electricity supply chain is resilient to geopolitical events and contributes to the fight against climate change. Given that in the present and for the near future natural gas-fired power plants will still play a role in setting wholesale electricity prices, especially when demand is high and/or when weather conditions limit renewable generation, it is of fundamental importance to diversify natural gas sources and routes, to ensure security of supply, and protect consumers from sudden gas and electricity price increases. A crucial role to achieve this goal will be played by the additional liquified natural gas infrastructure that is expected to be built in the next few years. However, in the long-run, the most important target will be that of creating a power sector based largely on renewable sources to achieve climate-neutrality targets and ensure consumers protections against sudden fuel price hikes. An increased renewable generation capacity will be really beneficial if adequate investments in interconnection capacity that allow cross-border electricity trades and in energy storage are made in parallel. Energy storage technologies will contribute to lower electricity prices during peak times, allowing excess electricity produced by renewable plants to be saved in large quantities and used later when it is most needed. In addition, expanding the capacity of and transparency of access to the electricity transmission grid is required to fully exploit the benefits of decentralised renewable generation. However, the green transition will also be exposed to geopolitical risk, given that solar photovoltaic panels, wind turbines, batteries, and electricity networks are all mineral-intensive technologies, and Europe heavily relies on imports from third countries for these raw materials. According to International Energy Agency (2023), the production of critical minerals is highly concentrated geographically, with the Democratic Republic of Congo supplying 70% of cobalt, China 60% of rare earth elements, and Indonesia 40% of nickel. The processing of these minerals is also highly concentrated, given that China is responsible for the refining of 90% of rare earth elements and 60-70% of lithium and cobalt. Finally, Europe also needs to expand its clean energy manufacturing production, which at present is largely outsourced. However, this poses another set of challenges given the lack of skilled labour and the aging population that have become a structural characteristics of this continent.

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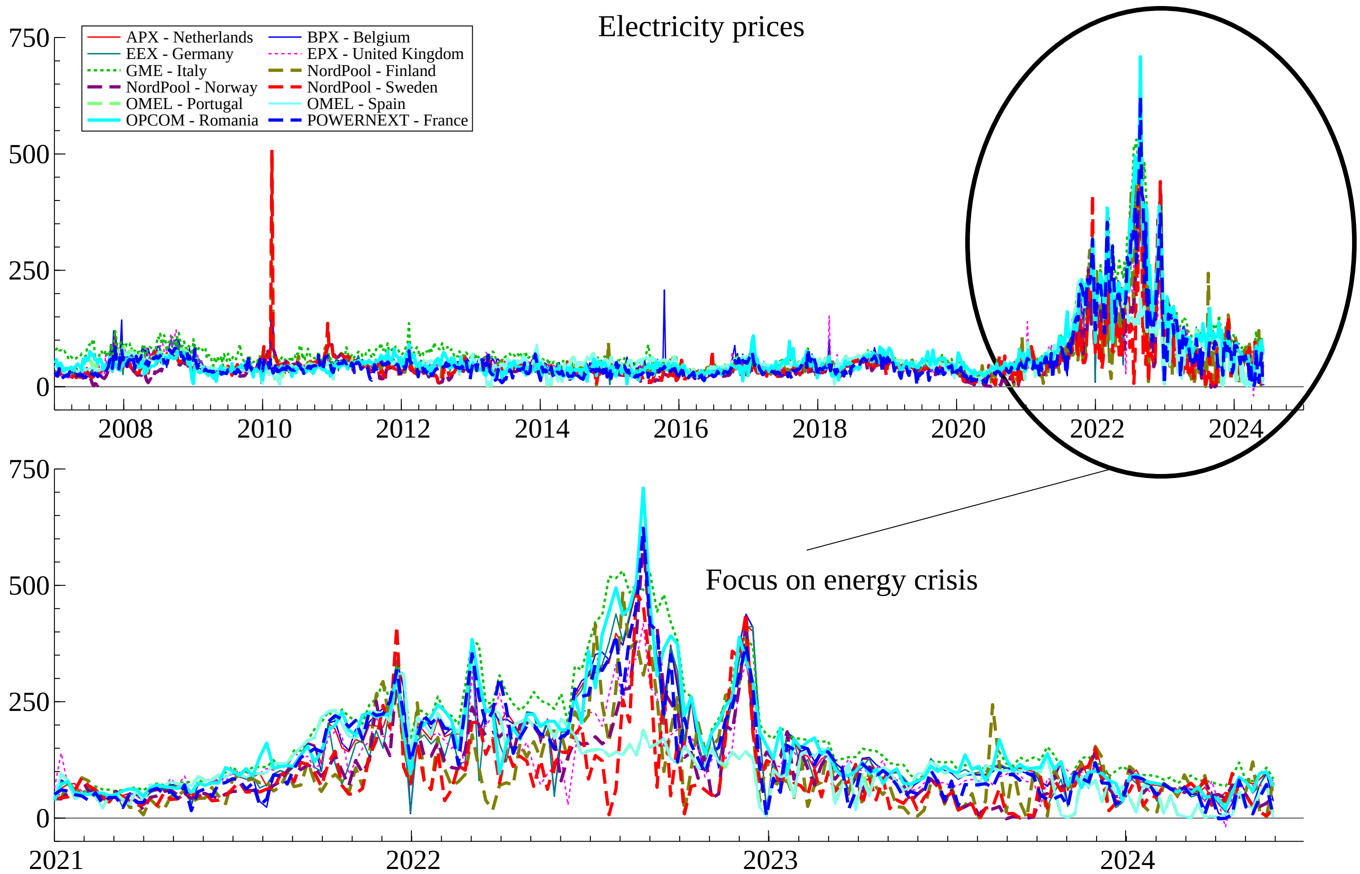
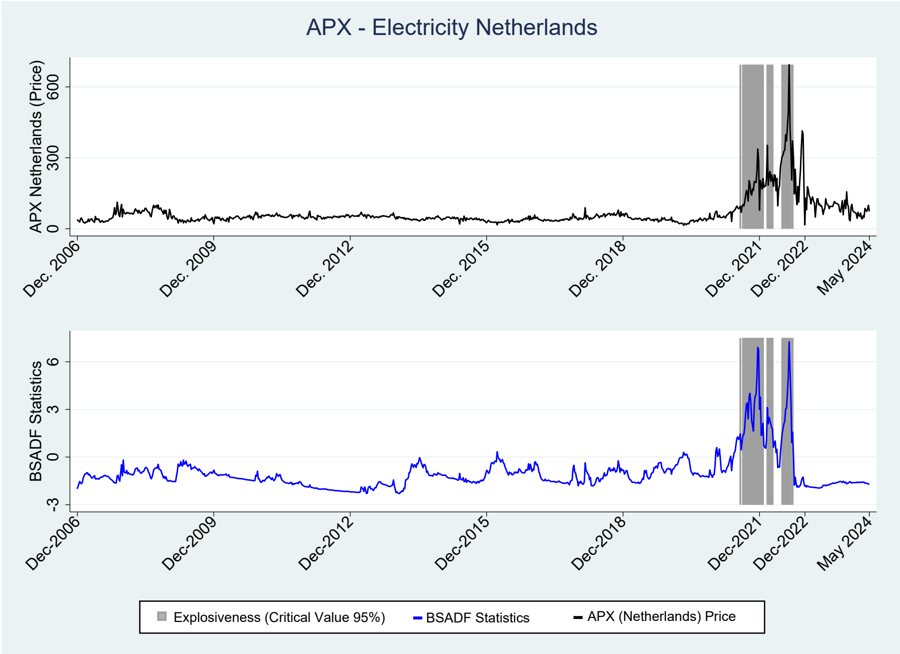
List of Figures

Figure 1: Wholesale day-ahead electricity prices and energy crisis.



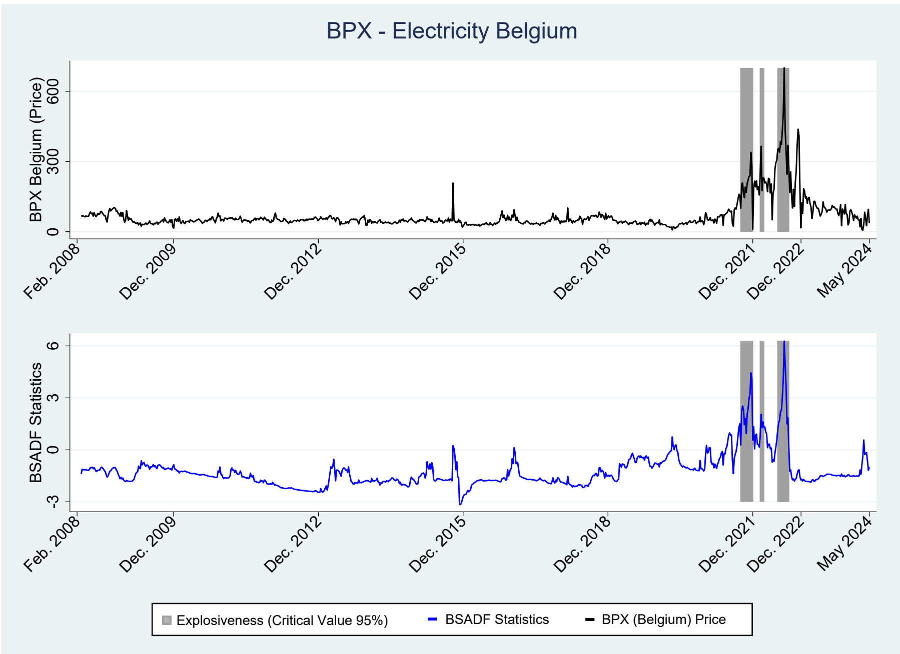
Source: Authors' elaboration on Refinitiv data.

Figure 2: BSADF test for APX Electricity Price Netherlands.



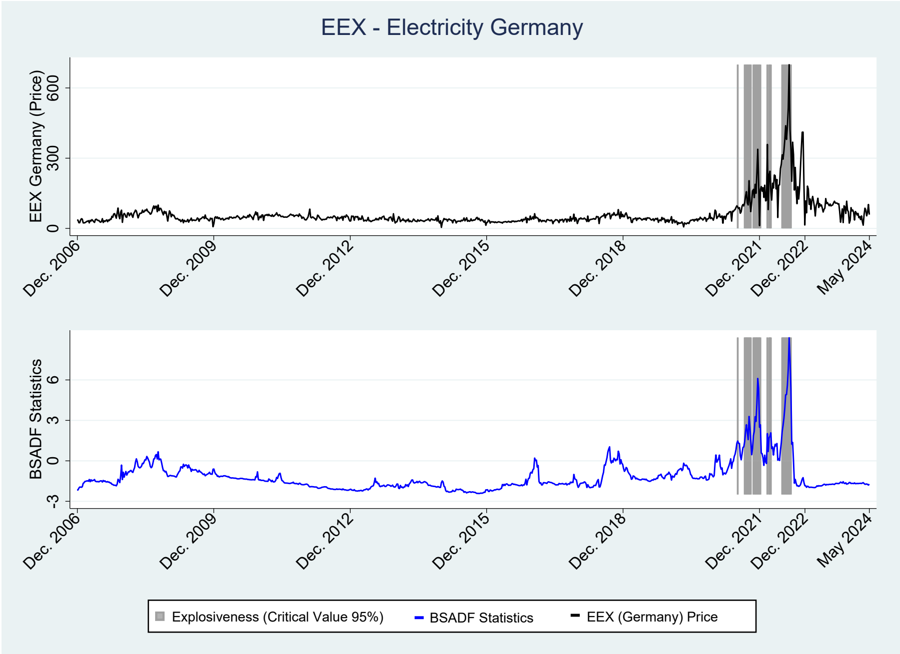
Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 910$ weeks.

Figure 3: BSADF test for BPX Electricity Price Belgium.



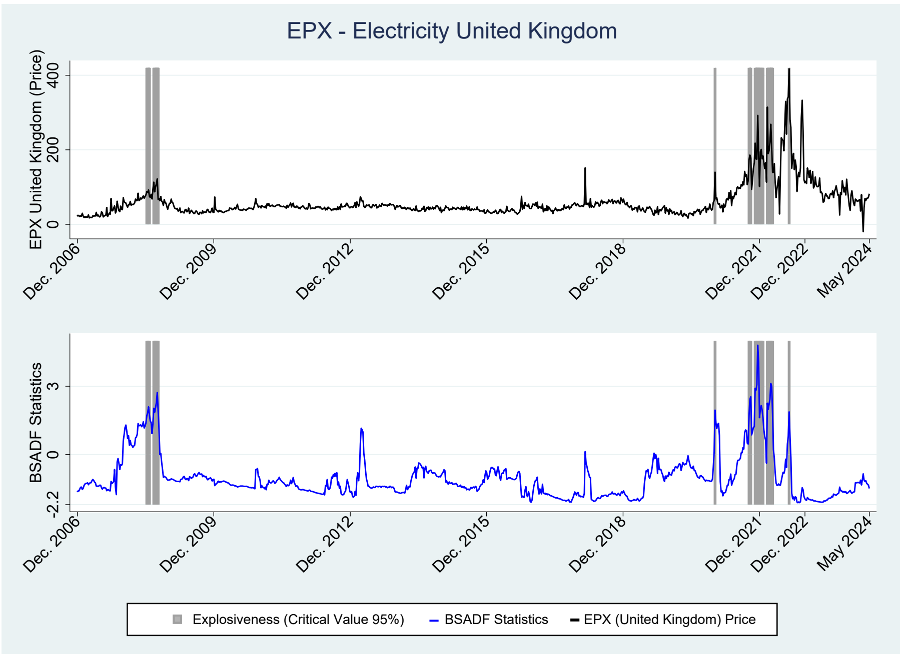
Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 853$ weeks.

Figure 4: BSADF test for EEX Electricity Price Germany.



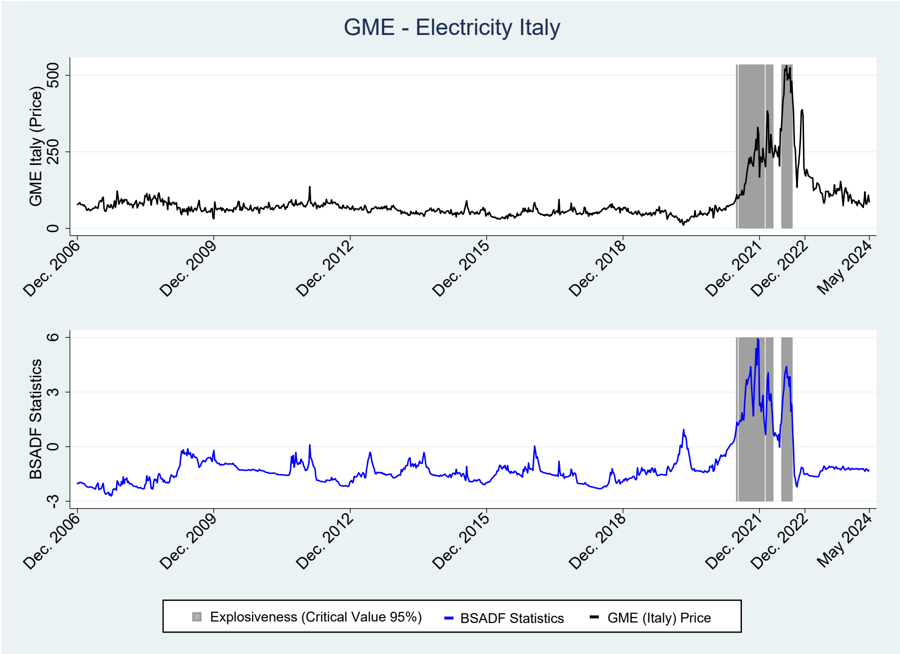
Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 910$ weeks.

Figure 5: BSADF test for EPX Electricity Price United Kingdom.



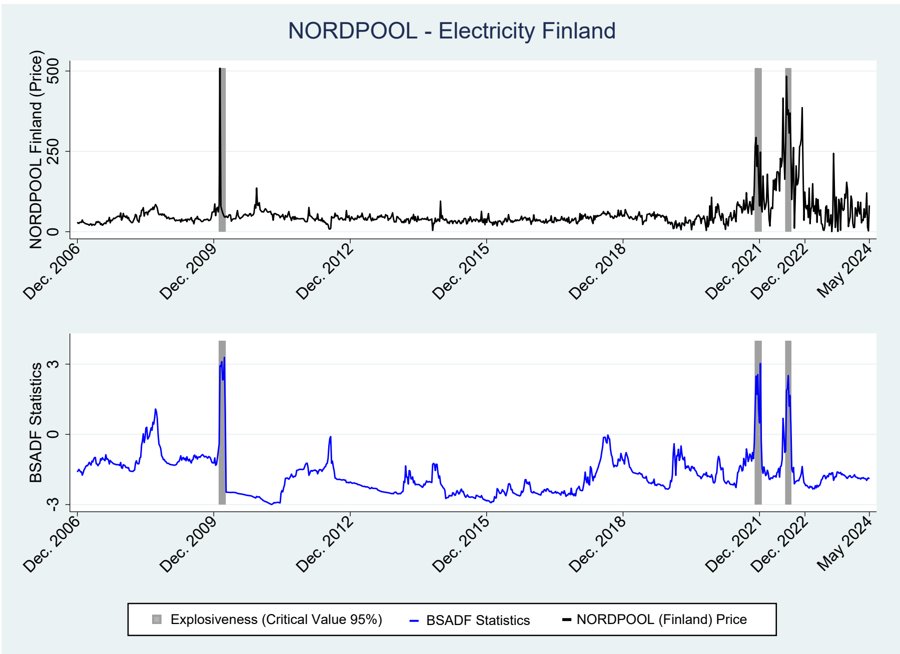
Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 910$ weeks.

Figure 6: BSADF test for GME Electricity Price Italy.



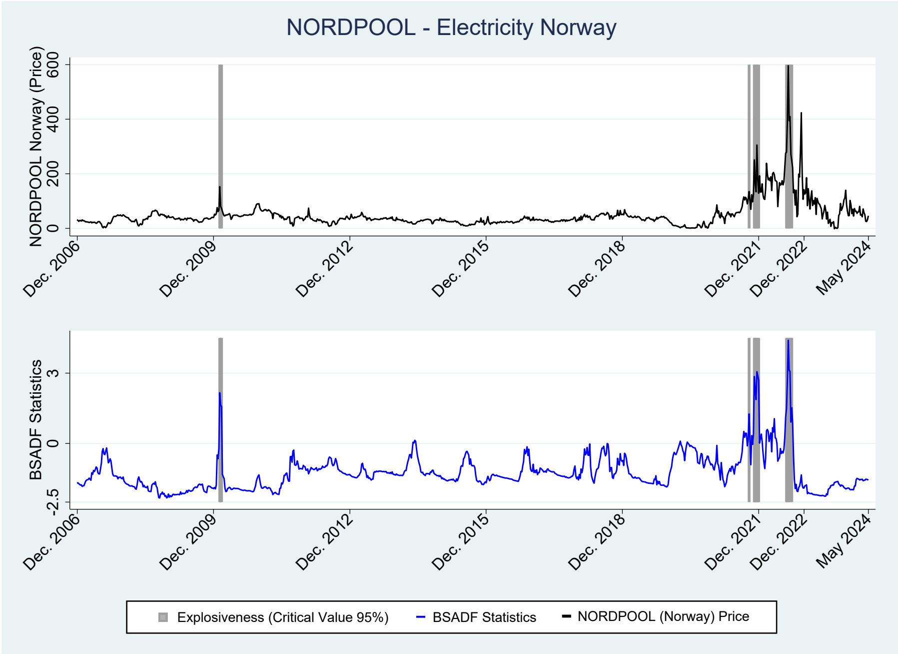
Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 910$ weeks.

Figure 7: BSADF test for NORDPOOL Electricity Price Finland.



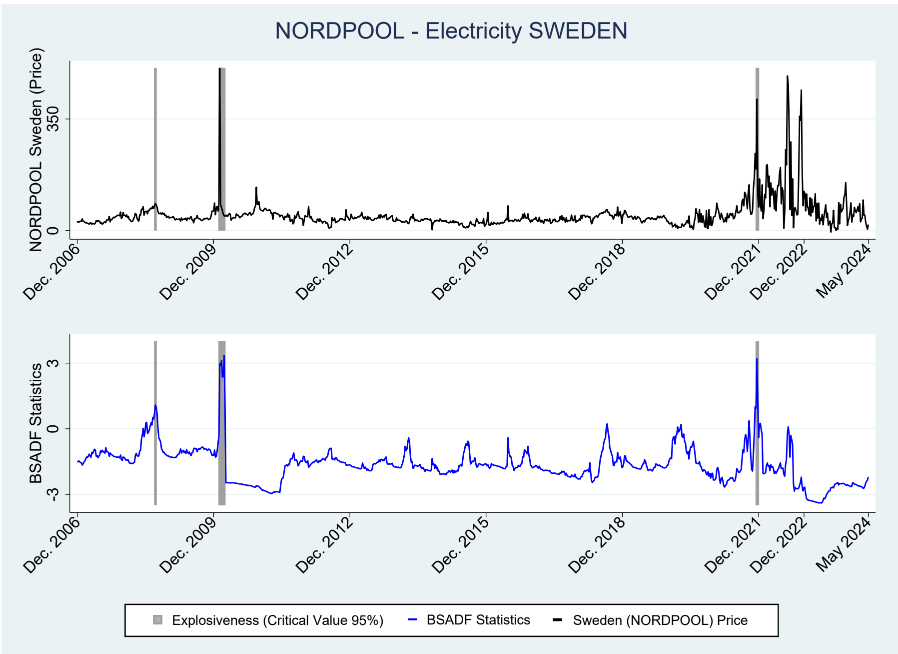
Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 910$ weeks.

Figure 8: BSADF test for NORDPOOL Electricity Price Norway.



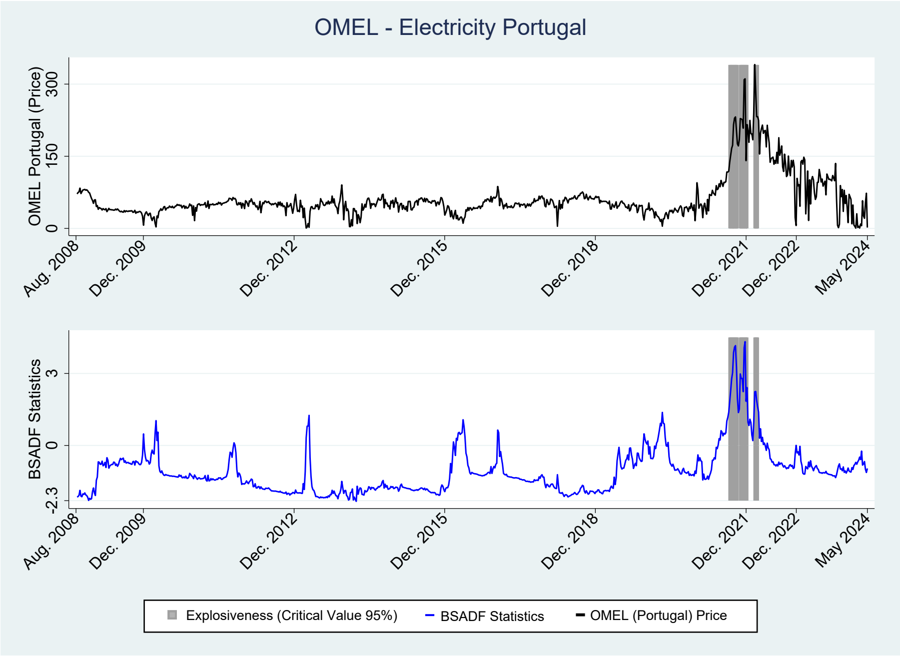
Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 910$ weeks.

Figure 9: BSADF test for NORDPOOL Electricity Price Sweden.



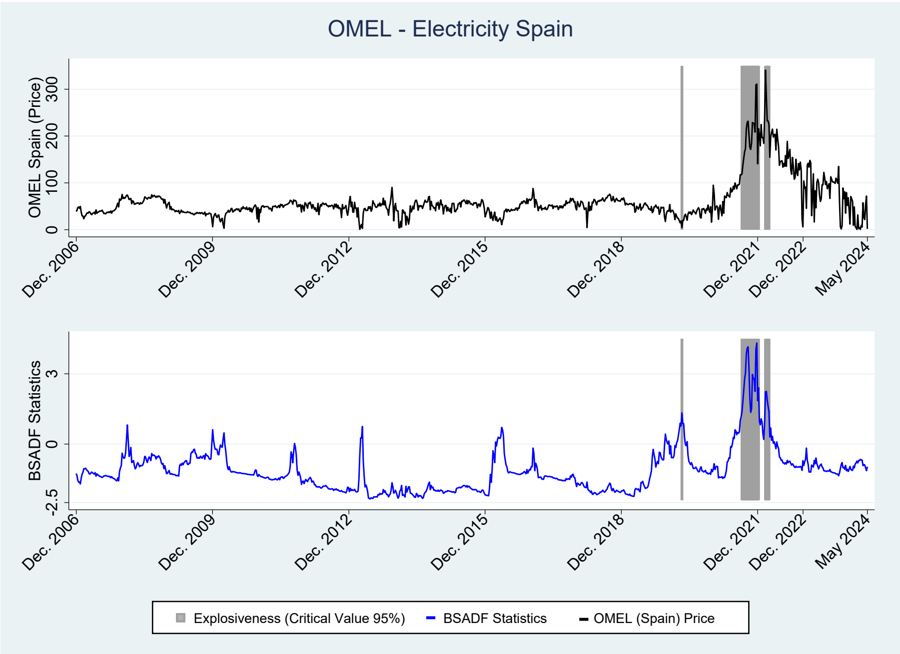
Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 910$ weeks.

Figure 10: BSADF test for OMEL Electricity Price Portugal.



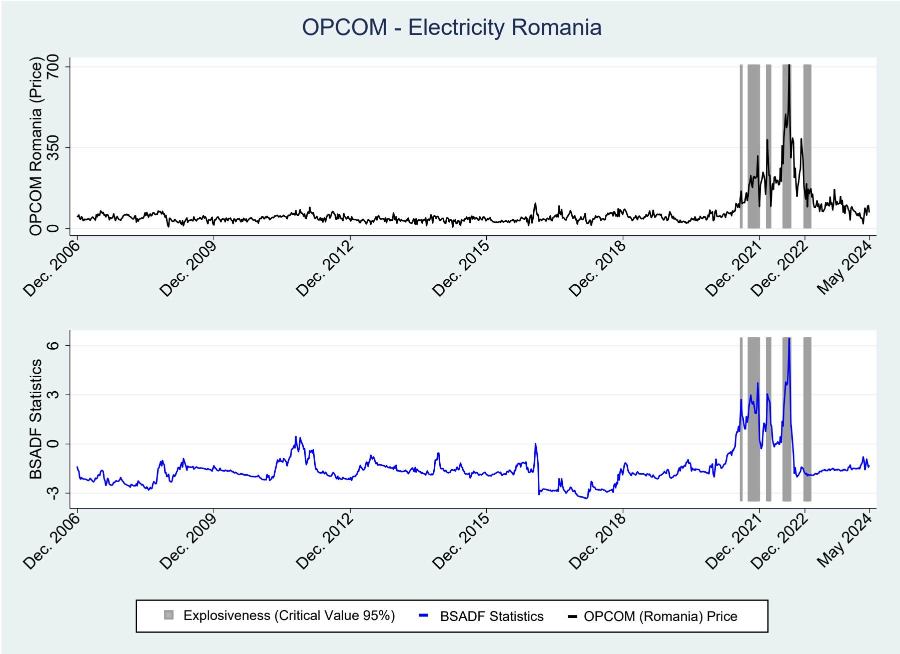
Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 822$ weeks.

Figure 11: BSADF test for OMEL Electricity Price Spain.



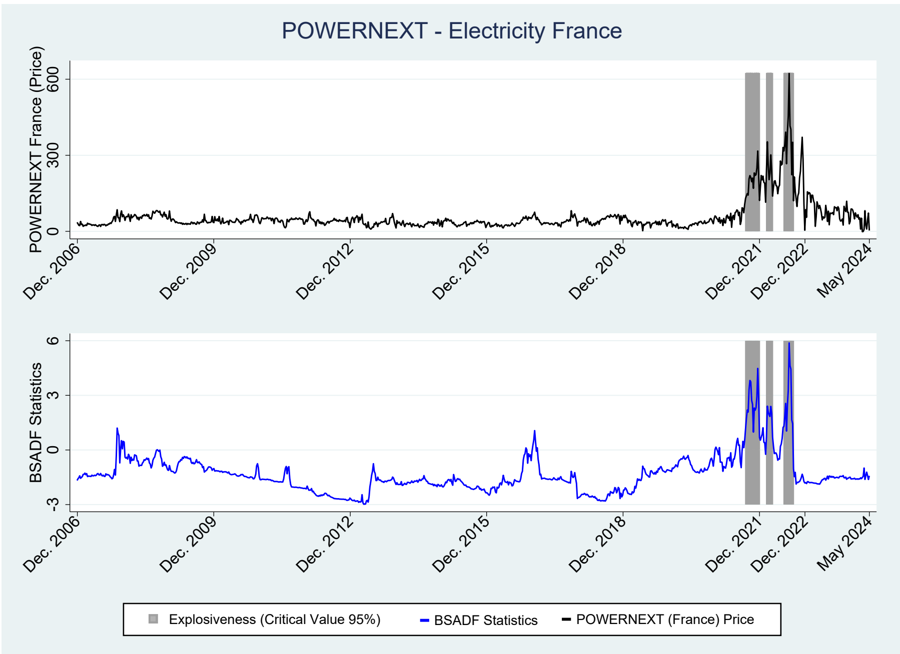
Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 910$ weeks.

Figure 12: BSADF test for OPCOM Electricity Price Romania.



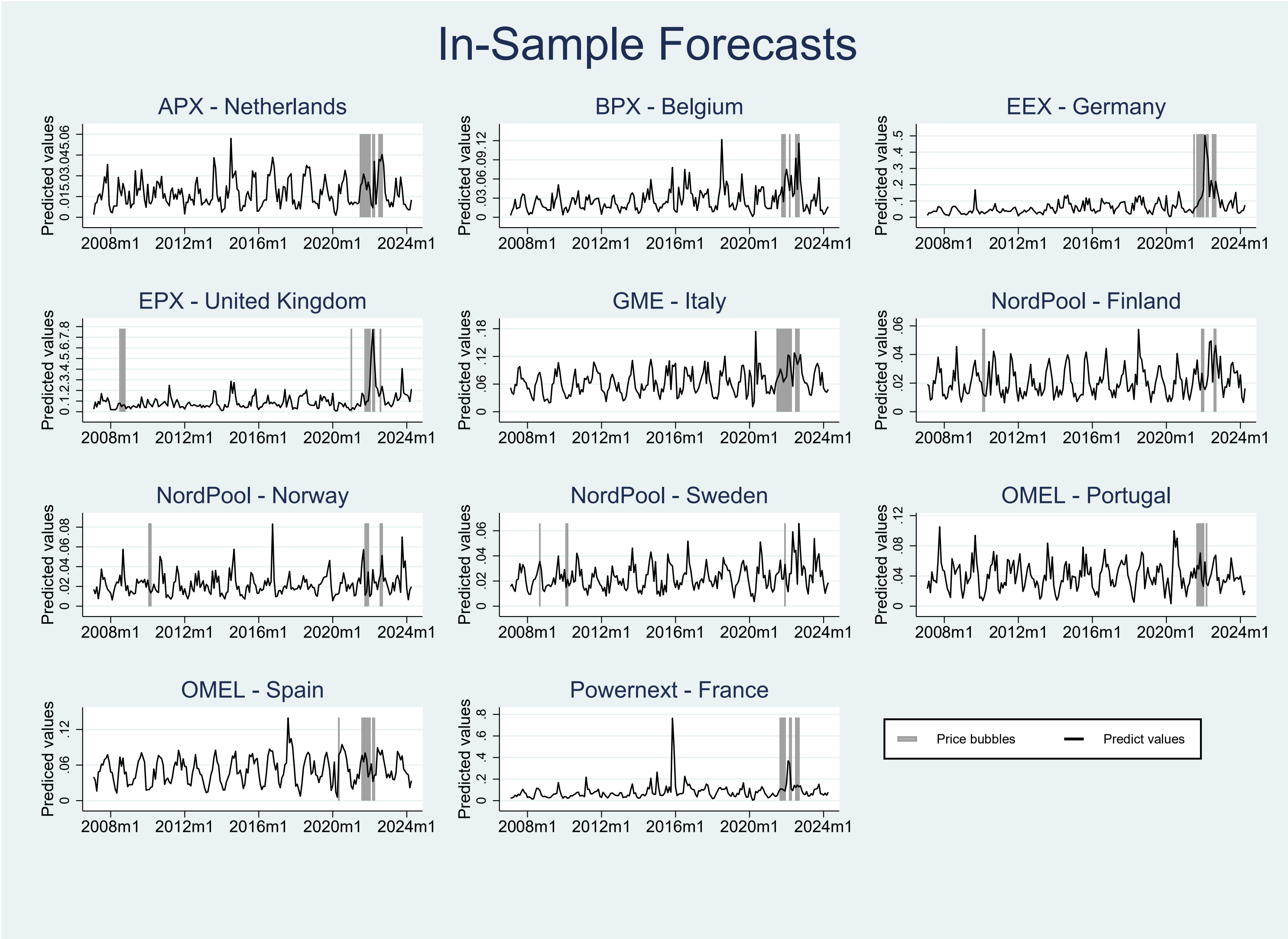
Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 910$ weeks.

Figure 13: BSADF test for POWERNEXT Electricity Price France.



Source: Authors' calculations on Phillips et al. (2015a, b) and Phillips & Shin (2020). $T = 910$ weeks.

Figure 14: In-Sample Forecasts.



The figure presents in-sample forecasts of price bubbles for the eleven electricity markets in Europe, over the time period 2007:2-2024:4. The line in each subplot shows the predicted probabilities of experiencing bubble episodes based on the underlying statistical model. The shaded areas show the periods of bubbles in electricity prices as identified by BADF tests.

List of Tables

Table 1: Descriptive statistics.

Variable		Mean	Min.	Max	Std. Dev.
APX - Netherlands	Price	65.45	14.14	693.83	60.91
	BSADF Statistic	-1.01	-2.30	7.25	1.14
BPX - Belgium	Price	67.66	5.93	700.41	64.33
	BSADF Statistic	-1.25	-3.16	6.28	1.00
EEX - Germany	Price	60.54	4.45	699.44	60.89
	BSADF Statistic	-1.17	-2.43	9.13	1.22
EPX - United Kingdom	Price	59.53	-19.64	417.22	45.32
	BSADF Statistic	-1.03	-2.12	4.80	0.97
GME - Italy	Price	84.52	10.66	531.06	70.33
	BSADF Statistic	-1.15	-2.71	5.93	1.20
NordPool - Finland	Price	54.11	0.35	508.75	50.23
	BSADF Statistic	-1.73	-3.00	3.29	0.89
NordPool - Norway	Price	48.27	-1.42	596.06	50.42
	BSADF Statistic	-1.23	-2.32	4.40	0.79
NordPool - Sweden	Price	48.57	-4.55	508.75	46.29
	BSADF Statistic	-1.63	-3.39	3.34	0.83
OMEL - Portugal	Price	61.15	0.59	340.70	43.98
	BSADF Statistic	-1.07	-2.33	4.32	0.99
OMEL - Spain	Price	59.76	0.59	340.70	42.15
	BSADF Statistic	-1.12	-2.34	4.32	0.95
OPCOM - Romania	Price	65.89	5.93	709.13	66.07
	BSADF Statistic	-1.59	-3.34	6.44	1.23
Powernext - France	Price	56.59	-1.33	622.97	59.99
	BSADF Statistic	-1.31	-2.98	5.88	1.09

The table reports the descriptive statistics for weekly electricity prices in the European countries and the BSADF statistics using the BSADF statistics for PSY (2015 a,b) test with bootstrap procedure proposed by Phillips & Shi (2020). The sample period is 31/12/2006 - 31/05/2024.

Table 2: Periods of bubbles for electricity prices.

Series name	**Country**	**Periods of bubbles**
		N. of weeks
APX	Netherlands	44
BPX	Belgium	22
EEX	Germany	33
EPX	United Kingdom	32
GME	Italy	50
NordPool - Finland	Finland	14
NordPool - Norway	Norway	16
NordPool - Sweden	Sweden	9
OMEL - Portugal	Portugal	21
OMEL - Spain	Spain	26
OPCOM	Romania	31
Powernext	France	29

The table reports the periods (n. of weeks) of bubbles for electricity prices in the European countries using the BSADF statistics for PSY (2015 a,b)' test with bootstrap procedure proposed by Phillips & Shi (2020). The time period is 31/12/2006 - 31/05/2024 (weekly frequency). The periods of bubbles are identified when the BSADF statistics exceed the 95% bootstrapped critical value, with n. bootstraps=499. The finite sample critical values for 95% confidence level is obtained from Monte Carlo simulations with 2,000 replications (see Phillips et al. (2015a, b) and Vasilopoulos et al. (2022)). The window size is given by $r_0 = \left(0.01 + 1.8/\sqrt{T}\right)$ as recommended by Phillips et al. (2015a,b).

Table 3: Timeline of energy crisis events and periods of bubbles in electricity prices.

Date and Events	Electricity prices - Periods of bubbles											
	APX Netherlands	**BPX Belgium**	**EEX Germany**	**EPX UK**	**GME Italy**	**NordPool Finland**	**NordPool Norway**	**NordPool Sweden**	**OMEL Portugal**	**OMEL Spain**	**OPCOM Romania**	**POWERNEXT France**
21/09/2021: International Energy Agency urges Russia to ramp up gas supply to Europe.	✓		✓		✓				✓	✓		✓
29/09/2021	✓		✓		✓				✓	✓		✓
06/10/2021	✓	✓	✓	✓	✓				✓	✓	✓	✓
13/10/2021	✓	✓	✓	✓	✓		✓		✓	✓	✓	✓
20/10/2021	✓	✓	✓	✓	✓				✓	✓	✓	✓
27/10/2021: President Putin orders Gazprom to fill Europe's gas storage only after Russia completes the filling of its own stocks.	✓				✓				✓	✓	✓	✓
03/11/2021	✓	✓			✓					✓	✓	✓
10/11/2021	✓		✓		✓					✓	✓	
17/11/2021	✓	✓	✓		✓				✓	✓	✓	✓
24/11/2021	✓	✓	✓	✓	✓		✓		✓	✓	✓	✓
01/12/2021	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓
08/12/2021	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓
15/12/2021	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
22/12/2021	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓
29/12/2021	✓		✓	✓	✓		✓		✓	✓		
05/01/2022	✓		✓	✓	✓	✓			✓	✓		
12/01/2022	✓			✓	✓							
19/01/2022	✓			✓	✓							
26/01/2022	✓			✓	✓							
02/02/2022					✓							

Table 3 continued from previous page

Date and Events	Electricity prices - Periods of bubbles											
	APX Netherlands	**BPX Belgium**	**EEX Germany**	**EPX UK**	**GME Italy**	**NordPool Finland**	**NordPool Norway**	**NordPool Sweden**	**OMEL Portugal**	**OMEL Spain**	**OPCOM Romania**	**POWERNEXT France**
22/02/2022: Germany halts certification of Nord Stream 2 pipeline and on 24 February, Russia invades Ukraine.					✓							
02/03/2022	✓	✓	✓	✓	✓				✓	✓	✓	✓
09/03/2022: Canada, UK and US anounce ban on oil and petroleum roducts from Russia.	✓			✓	✓				✓	✓	✓	✓
16/03/2022	✓	✓	✓	✓	✓				✓	✓	✓	✓
23/03/2022	✓		✓	✓	✓				✓	✓	✓	✓
31/03/2022: Russia introduces manadatory ruble payments for natural gas sold to "unfriendly" countries.	✓		✓	✓	✓					✓		✓
06/04/2022	✓			✓	✓							✓
13/04/2022	✓			✓	✓							
29/06/2022	✓		✓		✓							
11/07/2022: Nord Stream 1 interrupts flows of a 10 day period for annual maintenance.	✓		✓		✓							
13/07/2022	✓	✓	✓		✓						✓	
20/07/2022	✓	✓	✓		✓						✓	✓

Table 3 continued from previous page

Date and Events	Electricity prices - Periods of bubbles											
	APX Netherlands	**BPX Belgium**	**EEX Germany**	**EPX UK**	**GME Italy**	**NordPool Finland**	**NordPool Norway**	**NordPool Sweden**	**OMEL Portugal**	**OMEL Spain**	**OPCOM Romania**	**POWERNEXT France**
27/07/2022: EU member States agree on a voluntary reduction of natural gas demand by 15% during the 2022/23 winter season and Gazprom announces Nord Stream 1 gas flows to drop to 20% of its capacity.	✓	✓	✓		✓						✓	✓
03/08/2022	✓	✓	✓		✓	✓					✓	
10/08/2022	✓	✓	✓		✓	✓	✓				✓	✓
17/08/2022	✓	✓	✓		✓	✓	✓				✓	✓
26/08/2022: European natural gas benchmark TTF reaches a record high value of 339 €/MWh	✓	✓	✓	✓	✓		✓				✓	✓
01/09/2022: Gazprom announces indefinite shutdown of Nord Stream 1 pipeline.	✓	✓	✓		✓	✓	✓				✓	✓
07/09/2022	✓	✓	✓		✓		✓					✓
14/09/2022					✓							✓
21/09/2022	✓	✓					✓					✓

The table presents a timeline of major and key events related to the energy crisis (source: Emiliozzi et al. (2024)), along with the periods of bubbles determined using the BSADF statistics for the PSY (2015 a, b) test, employing the bootstrap procedure proposed by Phillips & Shi (2020). ✓stands for period of bubbles.

Table 4: Price bubbles and monthly indicators for country: summary statistics.

Country	**Description**	**Variables**				
		Geopolitcal Risk	**Air Temperature**	**Precipitation**	**Wind Speed**	**ΔIndustrial Production**
Belgium	Mean	0.18	283.61	0.08	3.92	0.12
	Min	0.02	271.77	0.00	2.67	-9.30
	Max	1.02	294.29	0.16	6.66	16.10
	Std. Dev.	0.15	5.55	0.03	0.73	3.05
Finland	Mean	0.04	276.13	0.06	3.31	-0.02
	Min	0.00	257.63	0.02	2.48	-13.50
	Max	0.55	292.84	0.14	4.31	7.40
	Std. Dev.	0.07	8.86	0.03	0.39	2.45
France	Mean	0.53	284.75	0.08	3.15	-0.07
	Min	0.19	273.27	0.02	2.36	-18.80
	Max	2.80	295.19	0.16	4.51	13.40
	Std. Dev.	0.32	5.80	0.03	0.43	2.66
Germany	Mean	0.44	282.89	0.07	3.28	-0.02
	Min	0.11	269.58	0.00	2.35	-20.20
	Max	2.66	293.76	0.17	5.50	9.60
	Std. Dev.	0.32	6.42	0.03	0.55	2.42
Italy	Mean	0.14	286.21	0.09	2.04	-0.14
	Min	0.03	274.55	0.01	1.31	-27.70
	Max	0.65	298.02	0.28	2.57	24.90
	Std. Dev.	0.09	6.64	0.04	0.24	3.38
Netherlands	Mean	0.08	283.83	0.07	4.24	0.00
	Min	0.01	271.77	0.00	3.02	-9.30
	Max	0.45	293.78	0.16	6.97	5.60
	Std. Dev.	0.06	5.44	0.03	0.74	2.11
Norway	Mean	0.05	275.66	0.11	2.75	-0.05
	Min	0.00	261.57	0.03	2.16	-10.80
	Max	0.47	289.45	0.22	3.54	12.00
	Std. Dev.	0.05	7.05	0.03	0.32	3.15
Portugal	Mean	0.02	288.48	0.06	2.95	-0.19
	Min	0.00	280.50	0.00	2.16	-22.90
	Max	0.24	298.53	0.26	4.45	11.50
	Std. Dev.	0.02	5.15	0.05	0.36	3.28
Romania	Mean	n.a.	283.64	0.06	2.39	0.16
	Min	n.a.	266.65	0.00	1.66	-27.80
	Max	n.a.	297.30	0.15	3.05	13.10
	Std. Dev.	n.a.	8.09	0.03	0.26	3.40
Spain	Mean	0.08	287.36	0.05	2.73	-0.13
	Min	0.02	277.81	0.01	2.03	-20.80
	Max	0.45	299.02	0.16	4.24	10.10
	Std. Dev.	0.05	6.27	0.03	0.38	2.66
Sweden	Mean	0.06	276.83	0.07	3.22	-0.02
	Min	0.01	261.29	0.01	2.49	-14.70
	Max	0.55	292.14	0.16	4.28	7.10
	Std. Dev.	0.07	7.80	0.03	0.37	2.50
United Kingdom	Mean	0.99	282.62	0.09	4.32	-0.05
	Min	0.44	272.84	0.02	2.84	-15.20
	Max	3.91	290.61	0.17	6.79	9.60
	Std. Dev.	0.40	4.20	0.03	0.71	1.81

The table reports the mean, minimum and maximum values, and standard deviation (Std. Dev.), respectively, for the *Price Bubbles*, *Geopolitical Risk*, *Air Temperature*, *Precipitation*, *Wind Speed* and Δ*Industrial Production*, for the countries considered over the time period 2006:12-2024:4. *Geopolitical Risk* is an indicator of geopolitical risk that measure the threat, realisation, and escalation of adverse geopolitical events in country i at time t (see Caldara & Iacoviello (2022)). For Romania, no data available for Geopolitical risk; *Air Temperature* is the ambient air temperature in Kelvin degrees measured at the height of 2 metres above the ground; *Precipitation* is the amount of rain, snow, sleet, or hail in metres that falls over a specific period of time in a particular area; *Wind Speed* is the wind speed in metres per second measured at the top of a 10 metres tower using an anemometer; Δ*Industrial Production* is the monthly change in the industrial production index.

Table 5: Determinants for Price Bubbles.

Dep. Variable: Price Bubbles$_{i,t}$	**Baseline**	**Average marginal effects**	**VIF**
	[i]	**[ii]**	**[iii]**
Geopolitical Risk$_{i,t}$	0.9418***	0.0823**	1.13
	(0.3127)	(0.0356)	
Air Temperature$_{i,t-2}$	0.0173*	0.0015*	1.12
	(0.0094)	(0.0009)	
Precipitation$_{i,t}$	-2.6538*	-0.2319	1.03
	(1.5246)	(0.1518)	
Wind Speed$_{i,t-1}$	-0.2614***	-0.0228***	1.25
	(0.0805)	(0.0077)	
ΔIndustrial Production$_{i,t}$	0.0286	0.0025	1
	(0.0184)	(0.0017)	
Constant	-5.9121**		
	(2.7634)		
N. Obs.	2,277		
Random Effects	Yes		
χ^2	23.95***		
BIC	795.27		

The table reports the estimation results of the panel probit model toghether with estimated marginal effects and VIFs. The dependent variable *Price Bubbles*$_{i,t}$ is a binary variable for price bubble in country i at time t. It takes the value 1 if BSADF tests indicate that prices in country i are in a bubble state and 0 otherwise; *Geopolitical Risk*$_{i,t}$ is an indicator of geopolitical risk that measure the threat, realisation, and escalation of adverse geopolitical events in country i at time t (see Caldara & Iacoviello (2022)); *Air Temperature*$_{i,t-2}$ is the ambient air temperature near to the surface, typically at height of 2 metres and measured by Kelvin degrees; *Precipitation*$_{i,t}$ is the amount of rain, snow, sleet, or hail (metres) that falls over a specific period of time in a particular area; *Wind Speed*$_{i,t-1}$ is the wind speed (metres per second) measured at the top of a 10 metres tower using an anemometer; Δ*Industrial Production*$_{i,t}$ is the monthly change in the industrial production index. Robust standard errors are reported in parentheses. Sample period: 2006:12–2024:4. *, **, *** denote the 10%, 5% and 1% significance level, respectively.

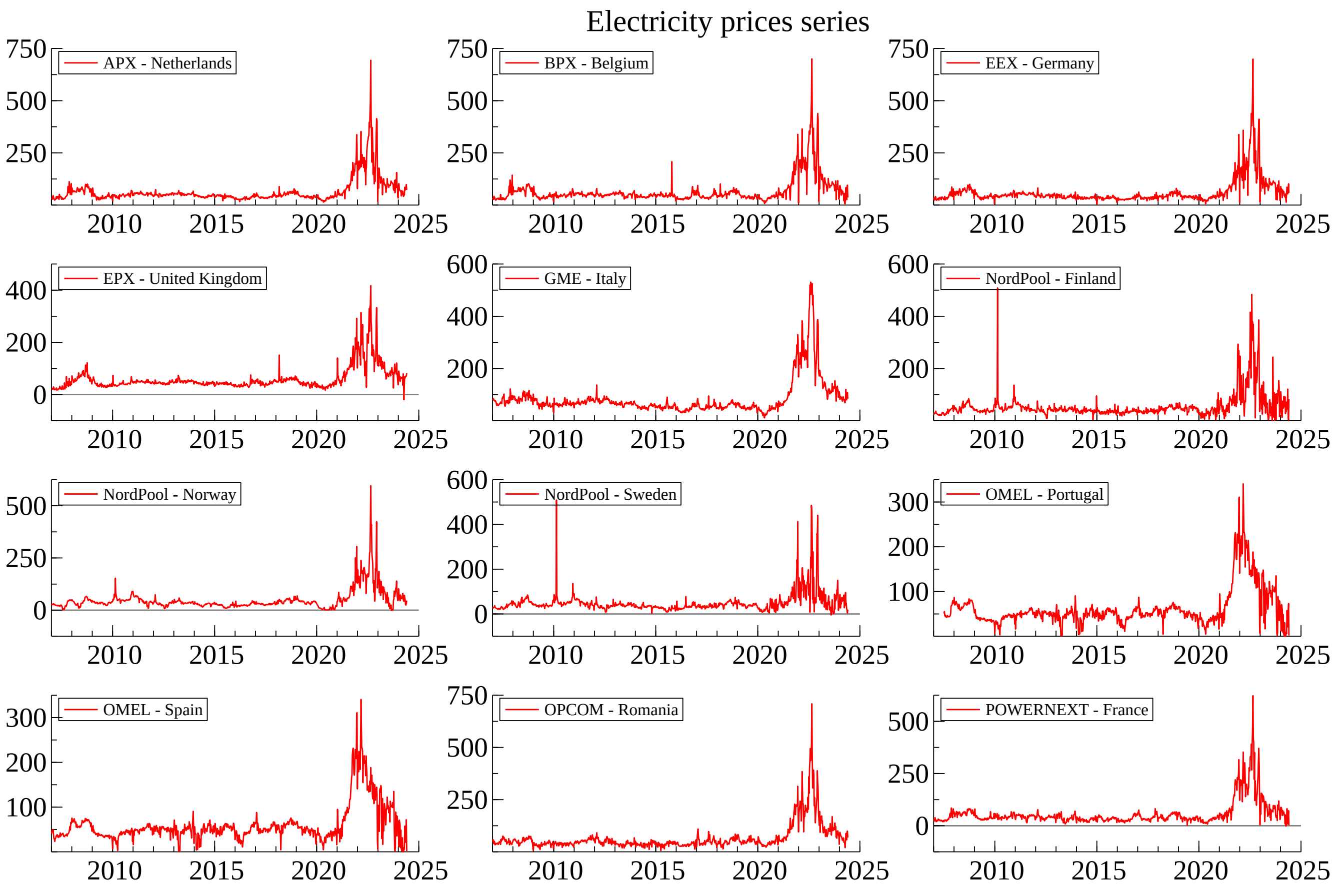
The role of geopolitical and climate risk in driving uncertainty in European electricity markets

January 24, 2025

Internet Appendix

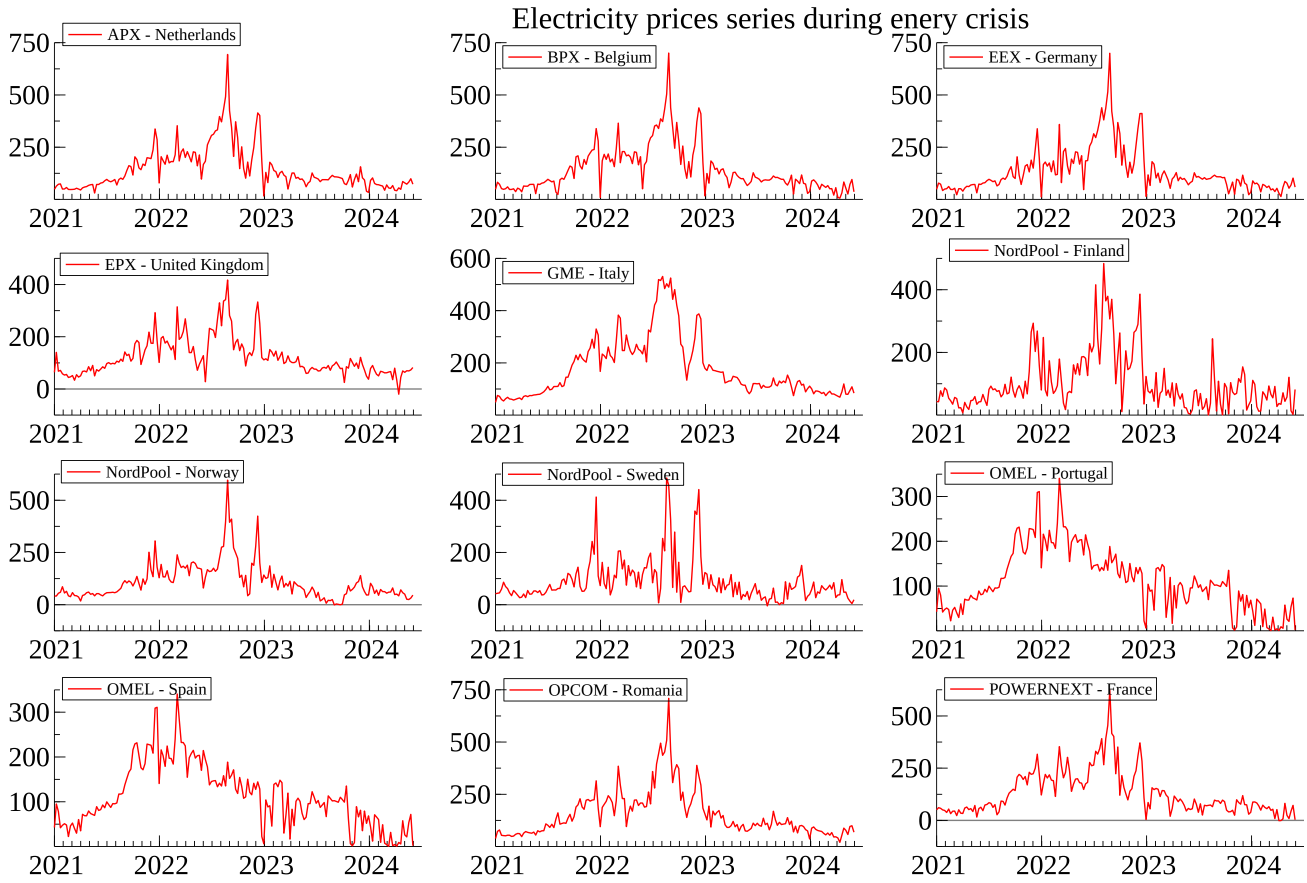
Appendix A Electricity Price Series

Figure A1: Electricity prices series.



Source: Authors' elaboration.

Figure A2: Electricity prices series and energy crisis.



Source: Authors' elaboration.

Appendix B Estimation of Bubbles Episodes

In this section, we report a detailed description for both the Backward Supremum Augmented (BSADF) approach (Phillips et al., 2015a, 2015b) (*A.1*) and for the BSADF computing using the bootstrap procedure (Phillips & Shi, 2020) (*A.2*).

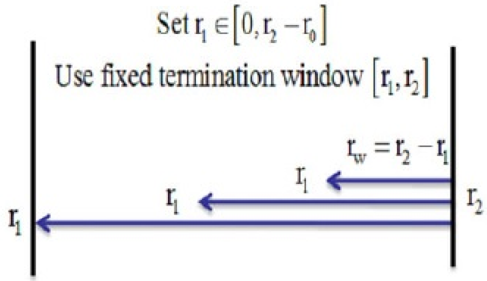
B.1 Backward Supremum Augmented (BSADF)

The Backward Supremum Augmented (BSADF) statistic is defined as follows:

$$BSADF_{r2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \left\{ BADF_{r_1}^{r_2} \right\} \tag{B1}$$

where r_1 and r_2 are the beginning and the ending fraction of the sample, with $r_1 < r_2$; r_0 is the fractional threshold and it is chosen on a lower bound of 1% of the full sample according to: $r_0 = (0.01 + 1.8/\sqrt{T})$, where T is the number of observations; r_w is the window size of the regression, as $r_1 - r_2$. Figure B1 shows how the BSADF works.

Figure B1: Recursive nature of the BSADF test.



Source: Phillips et al. (2015a, p. 1052).

Phillips et al. (2015a) apply the BSADF test on a sample sequence where the end point is fixed at r_2, and expands backwards to the starting point, r_1. Let r_e the fraction of the sample at which the period of bubble starts, r_f the fraction of the sample at which it ends, and $\hat{r}_e$ and $\hat{r}_f$ the estimators of both. The origination and termination points of a bubble, i.e. r_e and r_f, are computed according to the Equations (B2) and (B3):

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \left[r_2 : BSADF_{r_2}(r_0) > scv_{r_2}^{\beta} \right] \tag{B2}$$

$$and \quad \hat{r}_f = \inf_{r_2 \in [\hat{r}_e + \delta log(T), 1]} \left[r_2 : BSADF_{r_2}(r_0) < scv_{r_2}^{\beta} \right] \tag{B3}$$

where: T is the number of observations; $scv_{r_2}^{\beta}$ is the critical value of the BSADF statistic according to $\lfloor Tr_2 \rfloor$ observations and confidence level β; $\lfloor Tr_2 \rfloor$ refers to the largest integer smaller than or equal to Tr_2. According to Phillips et al. (2015a), a bubble exists if its duration must exceed a slowly varying (at infinity) quantity such as $L_T = log(T)$. This condition allows to exclude short lived blips and can be adjusted to consider the data frequency. Thus, $\delta log(T)$ is a minimal bubble length, and δ is a frequency-dependent parameter chosen freely.

B.2 BSADF using bootstrap procedure

Phillips & Shi (2020) use the bootstrap procedure to mitigate the potential influence of unconditional heteroscedasticity and to address the multiplicity issue in recursive testing.The bootstrap process combines two procedures: [i] Harvey et al. (2016); [ii] and Shi et al. (2020). Starting from the regression model for the PSY:

$$\Delta y_t = \mu + \rho y_{t-1} + \sum_{j=1}^{p} \phi \Delta y_{t-j} + \nu_t \tag{B4}$$

where: ν_t is assumed to satisfy $\nu_t \overset{i.i.d}{\sim} (0, \sigma^2)$; p lag terms of Δy_t are included for potential serial correlation. Let $\tau_0 = \lfloor Tr_0 \rfloor$ and τ_b be the number of observations in the window, then: [i] using the full sample period, the Equation (B4) is estimated under the imposition of the null hypothesis of $\rho = 0$, obtaining the estimated residual ε_t; [ii] for a sample size $\tau_0 + \tau_b - 1$, generate a bootstrap sample given by:

$$\Delta y_t^b = \sum_{j=1}^{p} \hat{\phi}_j \Delta y_{t-j}^b + \varepsilon_t^b \tag{B5}$$

with initial values $y_i^b = y_i$, with $i = 1, ..., j + 1$, and where the $\hat{\phi}_j$ are the OLS estimates obtained in the fitted regression from [i]. The residuals $\varepsilon_t^b = w_t \varepsilon_l$, where w_t is randomly drawn from the standard normal distribution and ε_l is randomly drawn with replacement from the estimated residuals ε_t; [iii] using the bootstrapped series, compute the PSY test statistic sequence $\{PSY_t^b\}_{t=\tau_0}^{\tau_0+\tau_b-1}$, and the maximum value of this test statistic sequence, giving:

$$\mathcal{M}_t^b = \max_{\tau \in [\tau_o, \tau_0 + \tau_b - 1]} (PSY_t^b) \tag{B6}$$

[iv] repeat steps [ii] and [iii] using $B = 499$ replications; [v] the critical value of the PSY procedure is given by the 95% percentile of the $\{\mathcal{M}_t^b\}_{b=1}^{B}$ sequence. Step [ii] computes a wild bootstrap to address heteroscedasticity, while steps [iii], [iv] and [v] replicate the PSY recursive test sequence and provide critical values that account for multiplicity in the test sequence recursion.

Appendix C Events of the Energy Crisis in Europe.

Table C1: Timeline of the energy crisis.

Date	Description of events
21/09/2021	International Energy Acency (IEA) urges Russia to ramp up gas supply to Europe.
27/10/2021	President Putin orders Gazprom to fill Europe's gas storage only after Russia completes the filling of its own stocks.
22/02/2022	Germany halts certification of Nord Stream 2 pipeline and on 24 February, Russia invades Ukraine.
08-10/03/2022	Canada, UK and US announce ban on oil and petroleum products from Russia.
31/03/2022	Russia introduces mandatory ruble payments for natural gas sold to "unfriendly" countries.
27/04/2022	Bulgaria and Poland are the first European countries cut off from Russian gas.
18/05/2022	European Union (EU) implements the REPowerEU plan to reduce dependence on Russian fossil fuels, promote energy savings and accelerate clean energy transition.
03/06/2022	EU announces an import ban on Russian seaborne crude oil and petroleum products.
08/06/2022	Fire at Freeport terminal impairs US LNG export capacity.
14/06/2022	Gazprom implements a reduction of gas supply via the Nord Stream 1 pipeline to 40% of its capacity.
11/07/2022	Nord Stream 1 interrupts flows of a 10 day period for annual maintenance.
26/07/2022	EU member States agree on a voluntary reduction of natural gas demand by 15% during the 2022/23 winter season and Gazprom announces Nord Stream 1 gas flows to drop to 20% of its capacity.
26/08/2022	European natural gas benchmark TTF reaches a record high value of 339€/MWh.
01/09/2022	Gazprom announces indefinite shutdown of Nord Stream 1 pipeline.
26/09/2022	Nord Stream 1 and 2 pipleine explosions and gas leaks.
05/10/2022	OPEC+ announces a 2 mln barrels a day production cut.
05/12/2022	G7 countries introduces a 60 USD/barrel price cap on Russian seaborne crude oil.
19/12/2022	EU agrees on the introduction of a price cap for natural gas at 180 €/MWh.
05/02/2023	G7 countries introduce a 100 USD/barrel price cap for premium-to-crude products and a 45 USD/barrel for discount-to-crude products.
31/03/2023	At the end of the European winter season, TTF benchmark quotes at 48 €/MHh, EU gas storage stands at 56%.

The table reports a timeline of major and key events related to the energy crisis (source: Emiliozzi et al. (2024)).

Appendix D Determining the Optimal Cut-Point

Table D1 provides an analysis of the optimal cutpoints for predicting price bubbles in electricity markets using three different methods: Liu's method (Liu, 2012), which selects the cut point that maximises the product of sensitivity and specificity; Youden's method (Youden, 1950), which selects the cut point that maximises the sum of sensitivity and specificity. It is used to find a balance where both sensitivity and specificity are maximised together; and the closest to (0,1) method, which finds the cut point that is closest to the top-left corner of the ROC curve, representing perfect sensitivity and specificity. We also bootstrap (1,000 replications) each cut point to estimate confidence intervals.

For each method, we report: [i] *the optimal cutpoint*: the threshold value that best separates positive outcomes (price bubbles) from negative ones; [ii] *sensitivity*: the proportion of true positives correctly identified (i.e., the ability to identify price bubbles correctly); [iii] *specificity*: the proportion of true negatives correctly identified (i.e., the ability to identify non-price bubbles correctly); [iv] *area under the ROC curve* (AUC): a measure of the overall performance of the classification model.

We conduct the analysis using the *predicted values* and the explanatory variables that were statistically significant in the probit analysis, including geopolitical risk, air temperature, wind speed, and Δindustrial production.

[INSERT SOMEWHERE HERE TABLE D1]

The *predicted values* provide a moderate level of accuracy in identifying price bubbles with balanced sensitivity and specificity. Geopolitical risk has a significant impact on price bubbles. The Liu and the closest to (0,1) methods provide similar optimal cutpoints with good sensitivity but moderate specificity. The Youden method has a higher sensitivity but lower specificity. Air temperature affects price bubbles, with the Liu and the closest (0,1) methods providing similar optimal cutpoints and balanced sensitivity and specificity; however, the optimal cutpoint is not statistically significant. The Youden method has higher specificity but lower sensitivity. Wind speed has a consistent optimal cutpoint across methods with moderate sensitivity and specificity. The AUC indicates moderate performance in predicting price bubbles. The optimal cutpoints for the ΔIndustrial production are never statistically significant apart from the closest (0,1) method, which provides balanced sensitivity and specificity.

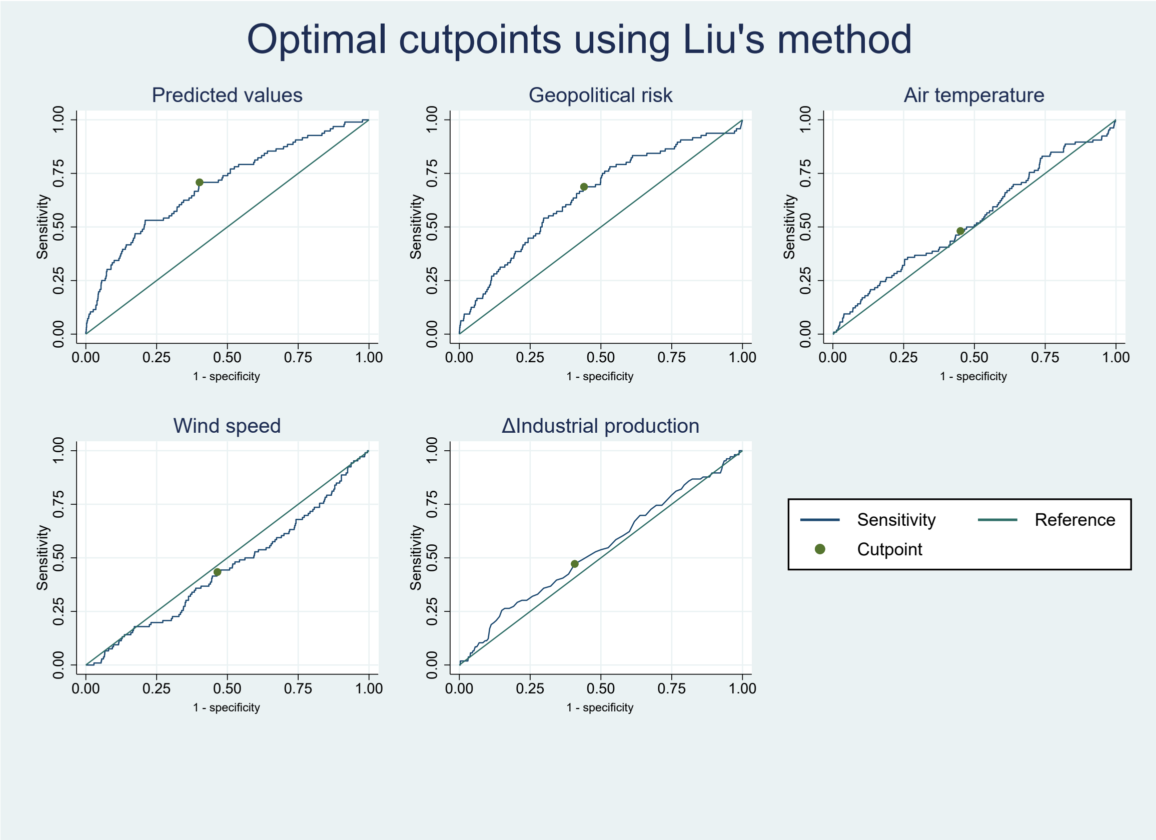
Figures D1-D3 illustrate the optimal cutpoints for predicting price bubbles using three different methods: Liu, Youden and the closest (0,1) methods. Each figure contains five subplots, corresponding to different explanatory variables: predicted values, geopolitical risk, air temperature, wind speed, and Δindustrial production. The ROC curves are plotted for each variable, showing sensitivity (true positive rate) on the y-axis and 1-specificity (false positive rate) on the x-axis. The green dot indicates the optimal cutpoint on each curve. The closest to (0,1) and the Liu methods generally provide similar optimal cutpoints with balanced sensitivity and specificity, while the Youden method tends to prioritise sensitivity over specificity.

Table D1: In-Sample forecasts - Computing the optimal cutpoint.

Reference variable	**Classification variable**	**Method**	**Optimal cutpoint**	**Sensitivity**	**Specificity**	**Area under the ROC curve**	*p*-**value**
			[i]	**[ii]**	**[iii]**	**[iv]**	
Price Bubbles	**Predicted values**	Liu	0.04***	0.71	0.60	0.65	0.00
		Youden	0.06***	0.53	0.79	0.66	0.00
		Closest to (0,1)	0.04***	0.71	0.60	0.65	0.00
	Geopolitical Risk	Liu	0.11**	0.69	0.56	0.62	0.03
		Youden	0.08	0.78	0.47	0.62	0.32
		Closest to (0,1)	0.12**	0.66	0.59	0.62	0.01
	Air Temperature	Liu	283.92***	0.48	0.55	0.52	0.00
		Youden	288.22***	0.35	0.75	0.55	0.00
		Closest to (0,1)	283.92***	0.48	0.55	0.52	0.00
	Wind Speed	Liu	3.14***	0.43	0.54	0.48	0.00
		Youden	3.93***	0.18	0.83	0.50	0.00
		Closest to (0,1)	3.14***	0.43	0.54	0.48	0.00
	ΔIndustrial Production	Liu	0.45	0.47	0.59	0.53	0.22
		Youden	1.85	0.25	0.85	0.55	0.12
		Closest to (0,1)	0.45*	0.47	0.59	0.53	0.09

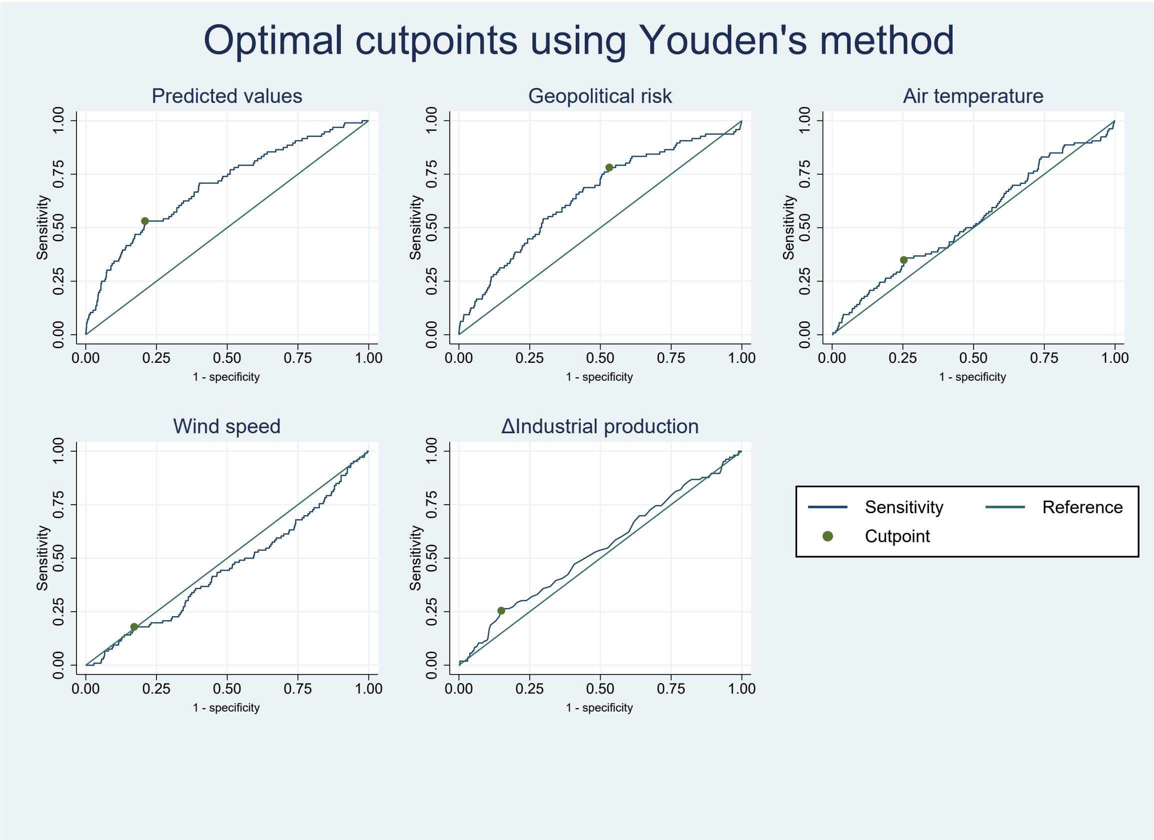
The table provides an analysis of the optimal cutpoints for predicting price bubbles in electricity markets using various methods. The classification variables used for predicting *Price Bubbles* include *Predicted values*, *Geopolitical Risk*, *Air Temperature*, *Wind Speed*, and *Industrial Production*. We use three different methods: Liu's method; Youden's method (Youden, 1950); Closest to (0,1). We also bootstrap (1,000 replications) each cut point to estimate confidence intervals. For each method, we report: [i] *the optimal cutpoint*; [ii] *sensitivity*; [iii] *specificity*; [iv] *area under the ROC curve* (AUC). Sample period: 2006:12–2024:4. *, **, *** denote the 10%, 5% and 1% significance level, respectively.

Figure D1: Optimal cutpoints using the Liu's method.



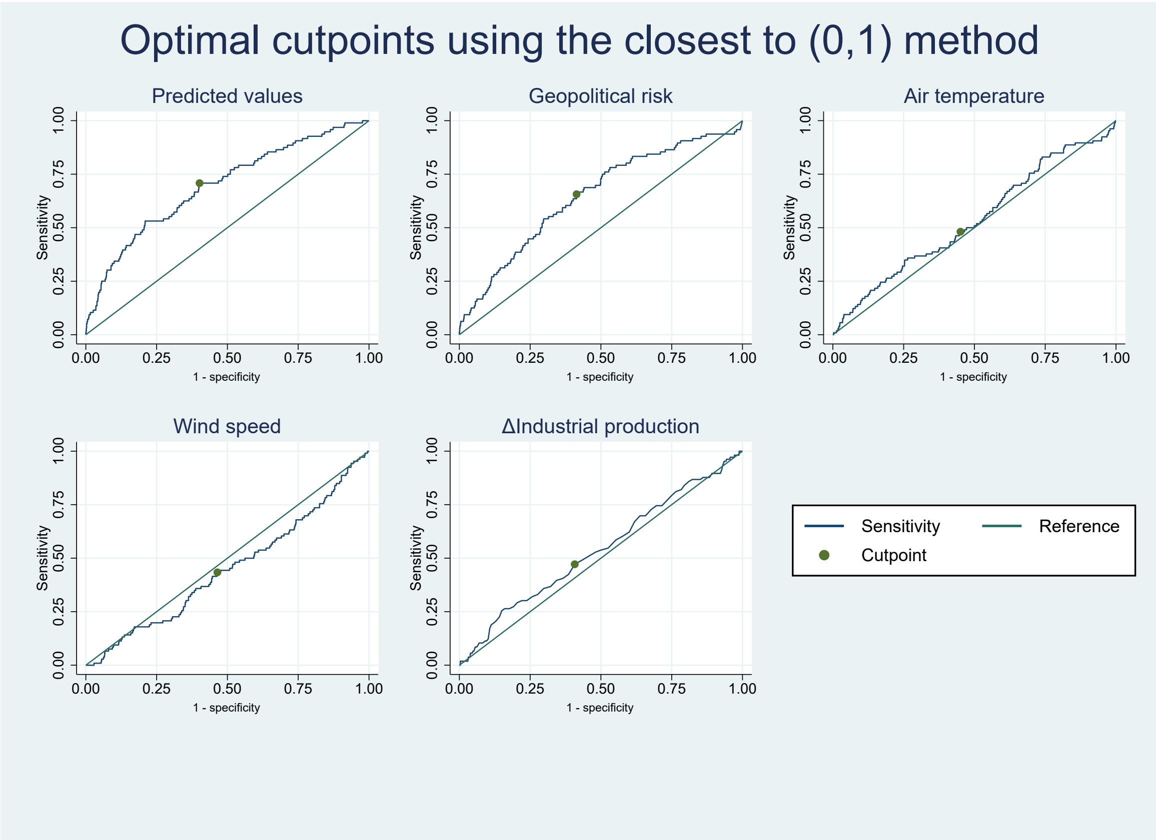
The figure presents sensitivity-specificity plots used to compute the overall performance of the classification model depending on the optimal cutpoints for predicting bubbles in electricity markets using Liu's (2012) method. The classification variables used for predicting *Price Bubbles* (0, 1), the binary variable where 1 indicates the presence of a price bubble and 0 indicates no bubble. The probability of price bubbles is plotted as a step function that alternates between 0 and 1; *Predicted Values*: these are the predicted probabilities of experiencing price bubbles based on the underlying statistical model. The values range between 0 and 1; *Geopolitical Risk* is an indicator of geopolitical risk that measure the threat, realisation, and escalation of adverse geopolitical events in country i at time t (see Caldara & Iacoviello (2022)); *Air Temperature* is the ambient air temperature near to the surface, typically at height of 2 metres and measured by Kelvin degrees (source: Copernicus); *Precipitation* is the amount of rain, snow, sleet, or hail (metres) that falls over a specific period of time in a particular area (source: Copernicus); *Wind Speed* is the wind speed (metres per second) measured at the top of a 10 metres tower using an anemometer (source: Copernicus); Δ*Industrial Production* is the monthly change in the industrial production index (source: Eurostat for European countries, Office for National Statistics for United Kingdom).

Figure D2: Optimal cutpoints using the Youden's method.



The figure presents sensitivity-specificity plots used to compute the overall performance of the classification model depending on the optimal cutpoints for predicting price bubbles in electricity markets using Youden (1950) method. The classification variables used for predicting *Price Bubbles* (0, 1), the binary variable where 1 indicates the presence of a price bubble and 0 indicates no bubble. The probability of price bubbles is plotted as a step function that alternates between 0 and 1; *Predicted Values*: these are the predicted probabilities of experiencing price bubbles based on the underlying statistical model. The values range between 0 and 1; *Geopolitical Risk* is an indicator of geopolitical risk that measure the threat, realisation, and escalation of adverse geopolitical events in country i at time t (see Caldara & Iacoviello (2022)); *Air Temperature* is the ambient air temperature near to the surface, typically at height of 2 metres and measured by Kelvin degrees (source: Copernicus); *Precipitation* is the amount of rain, snow, sleet, or hail (metres) that falls over a specific period of time in a particular area (source: Copernicus); *Wind Speed* is the wind speed (metres per second) measured at the top of a 10 metres tower using an anemometer (source: Copernicus); Δ*Industrial Production* is the monthly change in the industrial production index (source: Eurostat for European countries, Office for National Statistics for United Kingdom).

Figure D3: Optimal cutpoints using the closest (0,1).



The figure presents sensitivity-specificity plots used to compute the overall performance of the classification model depending on the optimal cutpoints for predicting price bubbles in electricity markets using Distance (0,1) method. The classification variables used for predicting *Price Bubbles* (0, 1), the binary variable where 1 indicates the presence of a price bubble and 0 indicates no bubble. The probability of price bubbles is plotted as a step function that alternates between 0 and 1; *Predicted Values*: these are the predicted probabilities of experiencing price bubbles based on the underlying statistical model. The values range between 0 and 1; *Geopolitical Risk* is an indicator of geopolitical risk that measure the threat, realisation, and escalation of adverse geopolitical events in country i at time t (see Caldara & Iacoviello (2022)); *Air Temperature* is the ambient air temperature near to the surface, typically at height of 2 metres and measured by Kelvin degrees (source: Copernicus); *Precipitation* is the amount of rain, snow, sleet, or hail (metres) that falls over a specific period of time in a particular area (source: Copernicus); *Wind Speed* is the wind speed (metres per second) measured at the top of a 10 metres tower using an anemometer (source: Copernicus); Δ*Industrial Production* is the monthly change in the industrial production index (source: Eurostat for European countries, Office for National Statistics for United Kingdom).