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# Time-varying systemic risk in electricity markets using generative adversarial networks: Market resilience and policy☆

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ABSTRACT

Current frameworks and policy instruments for monitoring and regulating European electricity markets fall short of fully addressing the complexities that arise during periods of market distress. Our study makes two key contributions in this area: First, it provides a novel, integrative analysis of systemic risk across 25 energy markets, encompassing oil, natural gas, and coal, as well as 21 European electricity markets. Second, it introduces Time Series Generative Adversarial Networks to systemic risk literature, enabling real-time tracking of market resilience. Our findings show that systemic distress in European electricity markets was higher in Q3 2021 than in late 2021 and early 2022, despite record-high electricity prices in the latter period, which many assumed reflected maximum market distress. This suggests that policy interventions enacted at the end of 2021 effectively reduced systemic distress in European electricity markets. However, fossil fuel markets reached a peak in risk during the first quarter of 2022, underscoring energy security concerns for Europe due to its reliance on foreign fuel sources, as prices are set in a global rather than regional context. Our modeling framework offers a tool to assess such risks in real time, providing valuable insights for proactive policymaking in the European energy sector.

## 1. Introduction

Although the necessity of considering systemic resilience in power market design has been emphasized at least since Wilson (2002), to the best of our knowledge, no prior attempt has been made to characterize systemic distress episodes in electricity markets.[1] Such an approach would ideally consider a sufficiently high number of power and other energy markets and provide quantifiable measures of market evolution during crises that can be used for policy evaluation and monitoring.

In recent policy debates, it is often assumed that the effectiveness of a policy should be directly measured by its impact on electricity prices. However, this is not necessarily the case. Policymakers should be concerned with reducing the likelihood of energy crises or systemic risk episodes. In this context, and with the aim of informing current and future policy discussions, particularly during the global energy transition, we propose an alternative approach.

We construct several time-varying indicators of systemic risk, which can be used to evaluate the effectiveness of interventions aimed at enhancing the resilience of energy markets, including electricity markets. Our research employs Generative Adversarial Networks (GANs) with a time-series structure (Yoon et al., 2019). These indicators allow us to uncover meaningful insights into recent episodes of market distress in European electricity markets and gauge the impact of policy interventions by the European Commission and national European governments in mitigating widespread fragility in these markets.

Systemic risk is traditionally defined in macro-financial literature as the risk faced by financial institutions during episodes of widespread distress triggered by a major negative market shock. This shock can result from the failure of an individual firm that is large or interconnected enough to impose significant distress costs on the broader

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[1] There is systemic risk literature regarding energy markets but is approached from a purely financial perspective. See the next section.

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system. Alternatively, systemic risk may arise from a common shock to the financial structure, amplified across firms according to their resilience (Acharya et al., 2017; Adrian and Brunnermeier, 2016; Jobst, 2014).

In our study, we shift the traditional focus of systemic risk modeling in finance from individual firms to entire markets, focusing on the upper quantiles of energy prices (when energy supply is at risk) rather than the lower quantiles typically associated with market fragility and portfolio losses in finance. Nonetheless, our model aligns with the branch of systemic risk literature that leverages market prices to assess market resilience in real time[2] (e.g., Acharya et al. (2017) and Adrian and Brunnermeier (2016)).

In the same fashion that the materialization of systemic risk episodes in the financial industry leads to significant disruptions in the provision of financial services that have adverse important consequences for the functioning of the real economy, the materialization of systemic risk in energy markets puts at risk the adequate functioning of whole modern economies that crucially depend on such markets to provide goods and services (see for example Algieri and Leccadito (2017), Murè et al. (2024) and Qin (2020)).

The importance of approaching risk from a system's perspective has recently re-emerged in Europe, following the extreme shocks the system faced in the second half of 2021 and 2022, primarily due to disruptions in the global supply of Russian natural gas. This, in turn, led to historically high electricity prices across Europe, driving energy bills and electricity supply uncertainty to unprecedented levels.

Lacking a sufficient understanding and adequate monitoring tools of energy market systemic distress on the side of policymakers constitutes a significant threat for households in or at the brink of energy poverty, for companies (including energy traders) facing the risk of bankruptcy due to unexpectedly large realizations of operational costs, and for the competitiveness of the industry, especially those sectors intensive in energy. Moreover, this situation jeopardizes the general population, as electricity is at the core of basic consumption and a main driver of inflation.

In summary, we make two key contributions to the literature. First, we are the first to study systemic risk scenarios in electricity markets from an integrative perspective, covering 25 energy markets—including oil, natural gas, coal, and 21 power markets. This approach allows us to capture not only systemic risk episodes in power markets but also their interactions with fossil-fuel markets, which are likely to determine electricity prices in the presence of supply or demand shocks. Second, we introduce TimeGANs to the systemic risk literature in economics, particularly energy economics, demonstrating how these recent advances in artificial intelligence (AI) can be leveraged to track market resilience in real time.

We quantify the effects of a comprehensive set of markets on wholesale electricity prices, which significantly influence the retail prices consumers pay. Unlike much of the existing literature, we focus on extreme scenarios where prices are exceptionally high and the system faces severe stress and uncertainty in electricity generation.

We estimate daily time-varying indicators. These indicators are designed to inform and support evidence-based policymaking by anticipating emerging threats to electricity systems (for instance, those related to fuel markets and market speculation), evaluating the worst possible outcomes after a major shock, measuring the resilience of the electricity market network, and testing potential policy mitigation strategies for short- and long-term energy objectives.

[2] As a branch of the financial literature, we assume that all relevant information is contained in the market prices, and therefore, we estimate systemic risk using only energy prices. We base our assumption on the fact that electricity prices are a function of weather variables and that all relevant information about renewable generation and demand is included in the prices (Mosquera-López et al., 2024).

Our indicators build on a branch of systemic risk literature in banking and finance (e.g., Hartmann et al. (2006) and Oh and Patton (2018)) and consist of two measures: the joint probability of distress (JPD), which assesses the likelihood that a large number of markets will experience distress simultaneously, and the expected proportion of markets in distress (EPD), which captures the heterogeneous dependencies between markets by measuring the proportion of markets in distress when one or more markets are already in distress.

Our empirical findings provide fresh insights. For instance, we show that European electricity markets experienced greater systemic distress in the third quarter of 2021 than in the first half of 2022, even though electricity prices reached all-time highs during the latter period. It appears that policy commitments from European authorities to intervene in electricity markets helped reduce systemic stress, particularly in power markets. However, this stabilizing effect did not spread evenly across electricity and fuel markets. Fuel markets, being global in nature, faced similar peaks in systemic risk in the first quarter of 2022 as they did in the second half of 2021. This highlights potential threats to European energy security due to its reliance on external fossil fuel sources.

The structure of this document is as follows: Section 2 provides a literature review to position our two key contributions within the broader context of risk spillovers in energy markets and the application of GANs in economics, finance, and energy. Section 3 details the methodology, which leverages advances in artificial intelligence developed initially in computer vision and natural language processing. Section 4 describes the data, Section 5 presents the results, and Section 6 discusses the conclusions and policy implications of our study.

## 2. Literature review

### 2.1. Systemic risk in energy markets

There is a significant gap in understanding the dynamics of energy markets during times of distress. The current design of electricity markets and the available policy tools fail to fully capture or address the complexities that emerge during periods of distress. The recent reform to the European electricity market design (European Commission, 2024a) attempts to manage such situations by allowing the European Council to declare a crisis when prices reach exceptionally high levels. In these cases, Member States may temporarily regulate retail prices below cost for vulnerable consumers, households, and small non-household consumers. The reform also promotes closer integration of the daily and intraday markets through enhanced cooperation between system and market operators, the reduction of the time between gate closure and dispatch to 30 min, and the potential creation of peak-shaving products or virtual hubs with regional reach (Fernández Gómez, 2024). However, current regulation does not explicitly account for systemic risk in electricity markets. Beyond its focus on high-priced episodes, it overlooks the potential for spillover effects across highly interconnected markets and the interdependencies with other energy sectors. This omission limits the ability of policymakers to anticipate and mitigate broader market disruptions and cross-sector instability that may arise during periods of widespread market distress.

In the academic literature, previous studies on systemic risk in energy markets and policy assessments have typically focused on one of the following aspects.

i) identifying optimal auction mechanisms for delivering and selling electricity in the wholesale market, including measuring consumer response, but primarily under regular market operations rather than during distress (e.g., Cicala (2022), Fowlie et al. (2021), and Reiss and White (2005));
ii) estimating market spillovers between energy commodities, financial markets from a financial risk management and asset allocation perspective, and broader macroeconomic conditions and policy indicators (e.g., Anwer et al. (2022); Choi et al. (2024);

Ji et al. (2018); Maneejuk et al. (2025); Marzioni et al. (2025); Mensi et al. (2021); Ouyang et al. (2022); Tiwari et al. (2021, 2025); Xie et al. (2024); J. Zhao et al. (2023));

iii) assessing interconnectedness and systemic risk spillover among traditional and clean energy firms and sectors (e.g., Hanif et al. (2025); Jin et al. (2024); Nadeem et al. (2025); Restrepo et al. (2018); Z. Wang et al. (2020); Wu et al. (2021); S. Zhou et al. (2025));

iv) analyzing systemic risk among a group of financialized commodity markets, like oil, natural gas, gasoline, livestock, metals, and agricultural commodities, considering the impact of major events like the Paris Agreement, COVID-19, the Russia-Ukraine conflict, or the impact of geopolitical risk (e.g., Huang et al. (2025); Jain and Maitra (2023); Syuhada et al. (2024); M.-T. Zhao et al. (2024));

v) providing a partial characterization of market distress episodes, typically focusing on a pair of energy markets or one at a time. For instance, oil and natural gas (e.g., Ben Ameur et al. (2022); Shen et al. (2018); T. Wang et al. (2025); E. Zhou and Wang (2023)), natural gas and electricity (e.g., Chuliá et al. (2024); Uribe et al. (2018, 2022)) or only electricity markets (e.g., Ahelegbey et al. (2025); Uribe et al. (2020)).

In sum, the systemic risk literature in energy economics has been approached primarily from a financial perspective. The analysis centers on financialized commodity markets, such as oil and natural gas, or on stock market prices of renewable and non-renewable companies. Even though some studies have explored risk spillover effects from natural gas, coal, oil, carbon renewables, and demand on electricity prices (e.g., Chuliá et al. (2019); Hirth, 2018)), to our understanding, the literature has not yet assessed systemic risk between power and other energy markets for a comprehensive set of European markets. Our study advances this line by adapting systemic risk approaches developed in finance—from individual firms or banks—to provide an integrative perspective on systemic risk in electricity and other energy markets.

### 2.2. Application of GANs in economics, finance, and energy

Since the introduction of GANs by Goodfellow et al. (2014), numerous variants and extensions have been developed to address specific problems, improve training stability, or handle particular types of data across different application areas. Although still at an early stage, the use of GANs and their variants in economics, finance, and energy is expanding, leveraging their ability to generate realistic synthetic data, model complex time series, and improve predictive accuracy (Dash et al., 2024). In this context, our paper also connects to this growing interest in the econometrics literature about the capabilities of deep learning to model economic systems due to the great flexibility offered by neural networks.

GAN models have been applied mainly in finance applications, including stock pricing forecasting (e.g., Gu et al. (2025); J. Wang and Chen (2024); R. Zhang and Mariano (2024)), asset (e.g., Chen et al. (2024)) and option pricing (e.g., Ge et al. (2025); Lv et al. (2025)), portfolio (e.g., Ramirez et al. (2023)) and trading (e.g., Mtetwa et al. (2023)) optimization, financial risk assessment and management (e.g., Allen et al. (2025); Chen (2024); Feng et al. (2022); J. Wang et al. (2024)), and credit and fraud risk management (D. Wilson and Azmani, 2026).

In the energy economics and green finance literature, there is a developing branch of studies that have used GANs, for instance, to complete imbalanced datasets in green growth prediction models (Abdelhady et al., 2024), predict load profiles (Claeys et al., 2024; Z. Wang and Hong, 2020), forecast oil prices (Haas et al., 2024; Kumari et al., 2025), model electricity prices scenarios taking into account temporal dynamics (Lu et al., 2022), predict real time locational marginal prices (Z. Zhang and Wu, 2022), model wind generation and market prices to optimize hybrid generation plants portfolios (Moradi-Sepahvand, 2025), construct renewable generation scenarios (Ye et al., 2024), and even map energy transition pathways (Luo et al., 2024).

While these studies demonstrate the versatility of GANs across energy economics applications, to the best of our knowledge, none have examined their potential for modeling systemic risk in power markets or, more broadly, in energy markets. To address this gap, we employ a model that explicitly accounts for the time-series structure of energy price data, unlike traditional GANs, which were initially designed to generate unseen images in computer vision tasks and lack a time dimension. To this end, we used a Time Series GAN structure advanced by Yoon et al. (2019) in the AI literature. This approach provides a high degree of flexibility to model the system's components and their interaction over time beyond the possibilities of traditional factor or copula models, both of which have been recently used in the systemic risk literature (Jain and Maitra, 2023; Mba, 2024; Ouyang et al., 2022; Tan et al., 2022; Tiwari et al., 2021; J. Zhao et al., 2023).

Our approach also offers several advantages over the systemic risk approach that uses copula models. Copula models in economics often rely on assumptions frequently unmet by the data. For example, time series data must be preprocessed to account for autocorrelation, trends, and seasonality, and conditional distributions for marginals must be assumed. Autocorrelation in time series can lead to false dependencies between variables, resulting in incorrect copula structures. Factor models account only for linear correlation, while autoregressive models limit random sampling without external conditioning. Time series have both static and temporal components, and the TimeGAN provides a more natural and flexible approach to generating scenarios that are consistent with the original data. We choose TimeGAN over other more recent GAN variants for modelling time series structures, as it delivers strong performance on synthetic data generation and has served as a benchmark for subsequent methods such as Conditional Time GAN (CTGAN) and Doppel GAN (DGAN) (Ang et al., 2023).

## 3. Methodology

Simulation for inference has been used for a long time (see Gelman and Rubin (1992)). In recent years, machine-learning techniques have enabled researchers to estimate more complex models that capture complex relations in the data. For example, when the underlying density function of the data is computationally intractable, deep neural networks can be used to generate data (Goodfellow et al., 2020). We use a Time Series Generative Adversarial Networks (TimeGAN) model that accounts for linear and nonlinear correlations between variables and time dependencies to generate over 1000 simulations of our energy prices dataset. We then use this generated data to estimate indicators of systemic risk. Using synthetic data allows us to estimate indicators as proportions rather than dichotomous variables, unlike when using observed data. This approach allows us to calculate quantiles and changes in systemic risk across time and markets, yielding smoother, more granular indicators. In other words, using synthetic data enables probabilistic estimation of systemic risk indicators, overcoming the limitation of real data being a single realization, in which systemic risk measures would otherwise take on values of zero or one. Moreover, Tavares et al. (2024) show that using synthetic data from TimeGAN to train results in 99 % similarity in model performance compared to a model trained on observed data.

### 3.1. Synthetic data generation

Generative Adversarial Networks avoid specifying a density function and learn only a tractable sample generation process. GANs are based on a game between two learning models —generally implemented using neural networks: the generator and the discriminator. The generator is defined by a prior distribution $p(z)$ over a vector $z$ that serves as input to the generator function $G(z;\theta(G))$, where $\theta(G)$ is a set of learnable parameters defining the generator's strategy in the game, the input vector $z$ can be considered a source of randomness in an otherwise deterministic system. The prior distribution $p(z)$ is typically a relatively unstructured distribution. The central role of the generator is to learn the function $G(z)$ that transforms $z$ into realistic samples $x$ (Goodfellow et al., 2014, 2020).

The other player in this game is the discriminator. The discriminator examines samples $x$ and returns some estimate $D(x;\ \theta(D))$ of whether $x$ is real (drawn from the training distribution) or fake (drawn from the generator). Each player incurs a cost $J^{(G)}\left(\theta^{(G)};\ \theta^{(D)}\right)$ for the generator and $J^{(D)}\left(\theta^{(G)};\ \theta^{(D)}\right)$ for the discriminator. Each player attempts to minimize its own cost. Roughly speaking, the discriminator's cost encourages it to classify data as real or fake correctly. In contrast, the generator's cost encourages it to generate samples that the discriminator incorrectly classifies as real (Goodfellow et al., 2014, 2020). Metz et al. (2017) show that this problem can be seen as the argument that minimizes:

$$J^{(G)}\left(\theta^{(G)}, \arg\min_{\theta^{(D)}} J^{(D)}\left(\theta^{(G)};\ \theta^{(D)}\right)\right) \tag{1}$$

However, this approach neglects the possible temporal correlation in the data, as it assumes *i.i.d.* in its simplest form. Therefore, we use the TimeGAN methodology proposed by Yoon et al. (2019) to address this issue. TimeGAN combines features from autoregressive models for sequence prediction, GAN-based methods for sequence generation, and time-series representation learning (Yoon et al., 2019). For time series data, we have static features, $S$, and temporal features, $X$. TimeGAN considers tuples $(S, X_{1:T})$, with joint distribution $p$. The length of $T$ is a random variable. Our goal is to use training data $\mathscr{D}$ to learn a density $\widehat{p}(S, X_{1:T})$ that best approximates $p(S, X_{1:T})$. To consider the temporal relationships in the data we can decompose the density into:

$$p(S, X_{1:T}) = p(S)\prod\nolimits_t p(X_t|S, X_{1:t-1}) \tag{2}$$

In addition to the generator and discriminator of the regular GAN, the model introduces two new networks: the embedding network and the recovery network. Together, these two new networks are called autoencoders. These autoencoders are an integral part of the proposed model since these networks capture the unknown locality of time series data (Asre and Anwar, 2022). The embedding and recovery functions provide mappings between feature — $S, X$— and latent space — $\mathscr{H}_s$, $\mathscr{H}_x$—, allowing the adversarial network to learn the underlying temporal dynamics of the data via lower-dimensional representations. The embedding function takes static and temporal features to their latent codes. In the opposite direction, the recovery function returns static and temporal codes to their feature representations.

In TimeGAN, the generator is exposed to two types of inputs during the training process. Fig. 1 shows the block diagram for this process.

First, the generator uses its previous outputs to generate the next synthetic vector. Then, the unsupervised loss and its gradient (given an initial value) are estimated. This will allow for maximizing (for the discriminator) or minimizing (for the generator) the likelihood of providing correct classifications for the training data and synthetic output. However, relying solely on the discriminator's binary adversarial feedback may not be sufficient incentive for the generator to capture the stepwise conditional distributions in the data. So, an additional loss to further discipline learning is introduced (the supervised loss). In an alternating fashion, the generator receives past sequences of embeddings of actual data to generate the next latent vector. Gradients can now be computed on a loss that captures the discrepancy between distributions. Applying maximum likelihood yields the supervised loss. Finally, the reconstruction loss is derived from the reconstructions from the latent to the feature space.

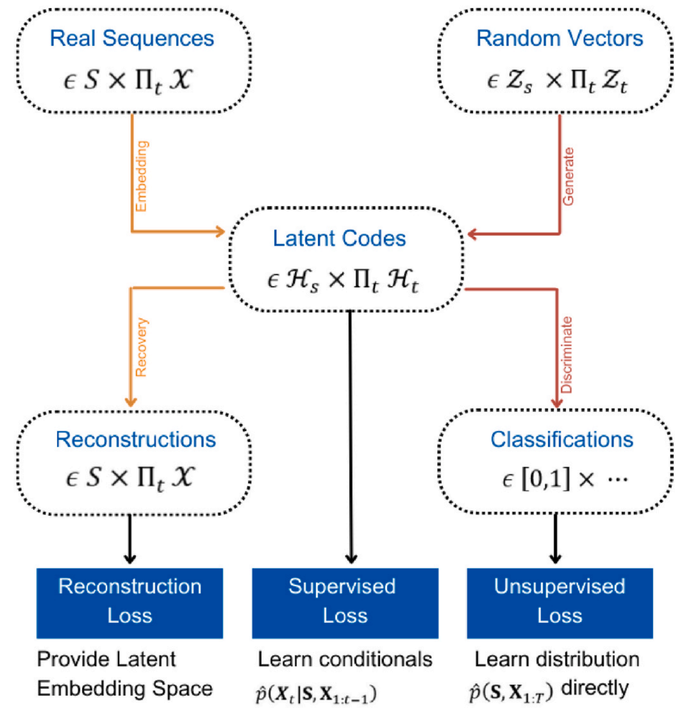



**Fig. 1.** TimeGAN component functions and objectives diagram.
Note: This figure shows the block diagram of component functions and objectives for TimeGAN based on Yoon et al. (2019). A TimeGAN consists of four network components: an embedding function, a recovery function, a sequence generator, and a sequence discriminator. The autoencoding components (the first two) are trained jointly with the adversarial components (the last two), so that TimeGAN simultaneously learns to encode features, generate representations, and iterate over time. It minimizes three types of loss: unsupervised (for correct classification of real and generated data), supervised (additional loss to further discipline learning), and reconstruction (from the latent to the feature space).

### *3.2. Systemic risk measures*

With the data generated from the TimeGAN, we proceed to estimate the indicators of systemic risk. The main advantage of using these generated data over the real data comes from the fact that, as the real data is only one realization, the indicators could only take the values of zero or one. Using the data generated, the resulting indicators are smoother and can show small changes in the values.

Following the approach of Oh and Patton (2018), first, we define a critical value that indicates distress as follows:

$$S_{i,t} \equiv 1\left\{Z_{i,t+250} > k^{*}_{i,t+250}\right\} \tag{3}$$

For every original energy price, the past year (250 days) is taken to define the 95th percentile ($k$); this is the level of distress when the price is in the extreme 5 % of the right tail. $k$ is dynamic and calculated with a mobile window of one day. With this, we construct a threshold series. Now, with the 1000+ synthetic series for every price, we count the number of times the simulated value was above the threshold each day.

Second, we use the probability that a large proportion of firms are in distress as a measure of systemic risk. The joint probability of distress (JPD) is defined as:

$$JPD_{t,k} \equiv Pr_t\left[\left(\frac{1}{N}\sum_{i=1}^{N} S_{i,t+250}\right) \geq \frac{c}{N}\right] \tag{4}$$

where $c$ is a threshold the user chooses for what constitutes a "large" proportion of series (N). Lastly, Equation (5) presents the expected proportion in distress (EPD). EPD calculates the proportion of the market in distress, given that one of the markets is in distress. We estimate this proportion not only for the whole market but also between sectors and intra-sectors (electricity or fossil fuels).

$$EPD_{i,t} \equiv E_t \left[ \frac{1}{N} \sum_{j=1,-i}^{N} S_{j,t+250} \middle| S_{i,t+250} = 1 \right] \tag{5}$$

The lowest value the measure can take is zero —i.e., only the ith variable is in distress—and the greatest is one —i.e., all markets are in distress—. This systemic risk indicator is conceptually similar to the CoVaR of Adrian and Brunnermeier (2016), since it considers distress "spillovers" from a single market to all energy markets or to a subset of them.

## 4. Data

In our estimations, we use 25 energy prices retrieved from Bloomberg and the European Network of Transmission System Operators for Electricity (ENTSOE), listed in Table 1. Our sample runs from January 1, 2015, to December 30, 2022, for a total of 2085 observations, with a daily frequency and limited to transaction days (weekdays).

Our variable set includes 21 electricity prices for all European countries, with data available for the period under analysis. All the prices are in EUR/MWh and correspond to the wholesale electricity market. Our variable set also includes four European fossil fuel prices to account for differences in generation mixes from thermal sources (see Figure A.1), as thermal plants are decisive in setting market prices in the presence of supply or demand shocks (Uribe et al., 2022). These include two natural gas prices —the Belgian Zeebrugge (ZEE) and the Dutch Title Transfer Facility (TTF); one coal price, the API2 index for coal imported into northwest Europe; and one crude oil price, the North Sea BFOE (Brent). Table 2 shows the summary statistics of the energy prices, and Figure A.2 in the Appendix depicts them (as well as the synthetic prices).

**Table 1**
Data.

| Market | Country/ Index | Units | Market | Country/ Index | Units |
|---|---|---|---|---|---|
| *Electricity* | Belgium | EUR/ MWh | *Electricity* | Norway | EUR/MWh |
| | Czechia | EUR/ MWh | | Portugal | EUR/MWh |
| | Denmark | EUR/ MWh | | Slovakia | EUR/MWh |
| | Estonia | EUR/ MWh | | Slovenia | EUR/MWh |
| | Finland | EUR/ MWh | | Spain | EUR/MWh |
| | France | EUR/ MWh | | Sweden | EUR/MWh |
| | Germany | EUR/ MWh | | Switzerland | EUR/MWh |
| | Greece | EUR/ MWh | | United Kingdom | GBP/MWh |
| | Hungary | EUR/ MWh | *Natural gas* | ZEE | GBP/ therm |
| | Italy | EUR/ MWh | | TTF | EUR/MWh |
| | Latvia | EUR/ MWh | *Coal* | API2 | USD/ metric tone |
| | Lithuania | EUR/ MWh | *Oil* | Brent | USD per barrel |
| | Netherlands | EUR/ MWh | | | |

Note: USD is US Dollars, EUR/MWh is euros per megawatt-hour, and GBP/therm is pounds per therm.

**Table 2**
Descriptive statistics.

| | Electricity | | | | |
|---|---|---|---|---|---|
| | Belgium | Czechia | Denmark | Estonia | Finland |
| Mean | 78.80 | 76.72 | 64.93 | 67.88 | 57.43 |
| Sds | 88.91 | 91.57 | 83.33 | 71.68 | 62.64 |
| Median | 45.96 | 43.05 | 37.75 | 42.31 | 38.57 |
| Min | −133.56 | −10.24 | −3.93 | 5.86 | 1.95 |
| Max | 700.41 | 703.26 | 699.44 | 682.05 | 501.45 |
| Range | 833.97 | 713.50 | 703.37 | 676.19 | 499.50 |
| Skewness | 2.86 | 3.04 | 3.49 | 3.37 | 3.82 |
| Kurtosis | 9.05 | 10.45 | 14.17 | 13.62 | 16.78 |

| | *Electricity* | | | | |
|---|---|---|---|---|---|
| | France | Germany | Greece | Hungary | Italy |
| Mean | 82.49 | 71.44 | 92.11 | 83.53 | 94.29 |
| Sds | 100.40 | 89.16 | 89.69 | 94.02 | 102.77 |
| Median | 45.14 | 39.56 | 56.93 | 49.03 | 55.19 |
| Min | 3.68 | −42.24 | 15.79 | 7.44 | 10.66 |
| Max | 743.84 | 699.44 | 697.41 | 748.97 | 718.71 |
| Range | 740.16 | 741.68 | 681.62 | 741.53 | 708.05 |
| Skewness | 2.88 | 3.12 | 2.63 | 3.04 | 2.74 |
| Kurtosis | 8.90 | 10.89 | 7.60 | 10.47 | 7.87 |

| | *Electricity* | | | | |
|---|---|---|---|---|---|
| | Latvia | Lithuania | Netherlands | Norway | Portugal |
| Mean | 75.06 | 85.92 | 75.66 | 55.74 | 71.64 |
| Sds | 84.98 | 96.38 | 86.41 | 72.10 | 55.80 |
| Median | 45.61 | 52.93 | 42.77 | 32.39 | 52.61 |
| Min | 5.86 | 10.21 | 5.15 | 0.94 | 2.02 |
| Max | 823.98 | 710.58 | 693.83 | 660.06 | 542.78 |
| Range | 818.12 | 700.37 | 688.68 | 659.12 | 540.76 |
| Skewness | 3.39 | 3.24 | 2.96 | 3.42 | 2.47 |
| Kurtosis | 13.36 | 11.58 | 9.76 | 14.46 | 7.78 |

| | *Electricity* | | | | |
|---|---|---|---|---|---|
| | Slovakia | Slovenia | Spain | Sweden | Switzerland |
| Mean | 79.06 | 87.21 | 71.62 | 49.56 | 84.26 |
| Sds | 93.83 | 98.07 | 55.78 | 57.51 | 99.25 |
| Median | 46.98 | 50.38 | 52.61 | 34.51 | 47.29 |
| Min | −21.00 | −7.30 | 2.19 | 1.64 | −5.79 |
| Max | 749.17 | 747.99 | 544.98 | 485.82 | 724.87 |
| Range | 770.17 | 755.29 | 542.79 | 484.18 | 730.66 |
| Skewness | 3.15 | 2.87 | 2.48 | 4.11 | 2.77 |
| Kurtosis | 11.52 | 9.13 | 7.83 | 20.10 | 8.12 |

| | *Electricity* | *Natural gas* | | *Coal* | *Oil* |
|---|---|---|---|---|---|
| | United Kingdom | ZEE | TTF | API2 | Brent |
| Mean | 75.26 | 72.71 | 33.35 | 98.77 | 62.76 |
| Sds | 73.48 | 84.28 | 42.30 | 75.48 | 18.73 |
| Median | 46.45 | 43.65 | 18.40 | 72.75 | 61.22 |
| Min | −10.13 | 10.10 | 3.00 | 39.25 | 19.33 |
| Max | 573.85 | 570.50 | 338.00 | 415.00 | 127.98 |
| Range | 583.98 | 560.40 | 335.00 | 375.75 | 108.65 |
| Skewness | 2.81 | 2.85 | 2.91 | 2.27 | 0.79 |
| Kurtosis | 9.17 | 8.57 | 9.43 | 4.46 | 0.74 |

Note: The table shows summary statistics for our data: Mean, Standard Deviation, Median, Minimum, Maximum, Interquartile Range, Skewness, and Kurtosis.

## 5. Results

Section 5.1 describes the synthetic data generation process and explains our selection of the specification that best fits our data. Section 5.2 presents our systemic risk estimates, aggregated across all markets and disaggregated by sector (i.e., electricity and fossil fuels). This section also includes an analysis of the systemic risk indicators to assess their dynamics during the European energy crisis. Finally, Section 5.3 provides systemic risk indicators estimated using subsamples of the data as a robustness exercise, which validates our main results.

### 5.1. Synthetic data generation

Table 3 first presents 12 possible specifications for the TimeGAN model to identify the best fit for our data. We vary the sequence length between 30, 60, 90, and 120 business days. The second hyperparameter we consider is the training batch size, which can take values of 128, 100, or 64. The third hyperparameter is the hidden dimension, which can be 112, 84, or 56. We keep the number of iterations fixed at 10,000 and the number of layers at three, following Yoon et al. (2019) to ensure convergence. Additionally, two traditional models were used to generate synthetic data: copulas and factors.

Table 3 also reports 13 performance metrics for each specification, following Ang et al. (2023) and Stenger et al. (2024). These are divided into eight model-based metrics that use synthetically generated series to train a post-hoc neural network, which is then tested on the original time series. These metrics include the discriminative score, accuracy, precision, recall, F1-score, Cohen's Kappa, ROC AUC, and the predictive score. Additionally, Table 3 presents four feature-based measures that aim to capture how well the synthetic data captures the inter-series correlation and temporal dependencies of the original data. These measures include the marginal distribution difference (MDD), the autocorrelation difference (ACF), the skewness difference, and the kurtosis difference. Finally, we include one visualization measure, t-SNE, which is a two-dimensional representation of the original and synthetic data.[3] This analysis reduces the dimensionality of the 25 energy prices considered in our model to two dimensions, where closeness between points implies that they are close neighbors or, in other words, that they are similar to each other.

The specification TimeGAN (30, 128, 112) has the best performance across the different metrics, ranking first on eight of them and never falling outside the top three. Based on these metrics, we confirm that the TimeGAN approach not only has advantages in terms of assumptions about the data that copula or factor models make, as discussed in Section 2, but that, with the correct specification, in this case using a sequence length of 30 days, this approach outperforms these traditional models used in the literature. We also note that longer sequence lengths do not imply better performance on the feature-based metrics, suggesting that shorter sequence lengths can still capture distributional characteristics, such as autocorrelation, of the original data.

### 5.2. Systemic risk indicators

The systemic risk indicators, joint probability of distress and expected proportion in distress, provide critical insights for regulators and market participants regarding the interconnectedness and potential for widespread failure within the market. The JPD, defined as the probability that a "large proportion" of markets are simultaneously in distress, signals to market participants when risk in the energy market becomes systemic. A high JPD indicates that distress is not confined to isolated segments but is likely to affect many markets concurrently. By tracking JPD dynamics, buyers and sellers of electricity can anticipate such conditions and implement hedging strategies, such as signing power purchase agreements (PPAs) or adjusting their positions in futures markets.

While JPD measures the likelihood of a simultaneous market failure, the EPD captures distress spillovers by calculating the proportion of the market in distress given that one market is in distress. This indicator, therefore, reflects the severity and source of market distress. In turn, it enables market participants to obtain more detailed information about the origin and propagation channels of systemic risk. For policymakers, JPD acts as a crucial early warning signal for regulatory action. A high or rising JPD indicates that the overall market structure is prone to multiple simultaneous failures, exceeding the predefined distress threshold. Meanwhile, monitoring changes in EPD allows policymakers to understand how quickly and broadly systemic risk can propagate from a single point of failure.

The simulations from the multivariate distribution learned by the TimeGAN reported in the previous section were used to obtain these time-varying systemic risk indicators. Fig. 2 presents the JPD considering a threshold (c) of 30 % (at least eight markets). We find similar results with $c = 20\%$ and $c = 40\%$. The joint probability of distress from 2016 to 2020 shows that, on average, there was a 23 % probability of at least eight markets experiencing distress, with the lowest probabilities recorded in 2019 and the first three quarters of 2020. This trend aligns with the drop in energy prices during the pandemic, especially in early 2020, when global economic activity and energy demand declined sharply. The JPD almost doubled in 2021 and 2022 compared to pre-crisis levels, consistent with the surge in global energy commodity prices. This price increase was partly due to a resurgence in demand for oil, gas, and electricity as economic activity and travel resumed, and partly due to supply constraints. OPEC+, having reduced oil output due to low demand at the pandemic's onset, faced challenges in meeting production targets after agreeing in 2021 to restore output gradually (Kuik et al., 2022).

In Europe, gas storage levels were not fully replenished over the summer of 2021 due to several factors: an unusually cold prior winter, reduced supply from Norway early in the year because of maintenance issues, and lower gas exports from Russia. Additionally, low wind levels during the warmer months meant that wind-generated energy had to be supplemented by gas-fired power. In financial terms, gas derivative trading is highly concentrated, and short positions from the top five companies surged by 200 % between February and November 2022, intensifying market volatility and the price shock (European Commission, 2024b). All these factors contributed to the surge in natural gas prices that created a spillover effect on the demand for other fossil fuels, such as coal and oil, which serve as substitutes for electricity generation and heating. Moreover, Kuik et al. (2022) estimated that the pass-through of natural gas prices to gas-fired electricity was at least 85 % from July 2021 to April 2, 022.[4] Additionally, in 2022, France had to take more than half of its nuclear reactor fleet offline for maintenance and safety issues, affecting the European electricity supply. Traditionally a net exporter of electricity, the country had to import more electricity than it exported that year (GRS, 2023).

The demand and supply shocks in energy commodities during 2021 are reflected in our systemic risk indicator, as the JPD spiked, with probabilities exceeding 95 % for a significant portion of the series being in distress during the second semester. On average, the JPD for 2021 was 68 %. Energy commodity prices continued to rise in 2022, driven by the Russian invasion of Ukraine in February, which further heightened volatility and prices already strained by low gas inventories and France's electricity supply shock. However, the JPD reached higher values more times in 2021 than in 2022, even though electricity prices reached record highs in the latter year. This suggests that, while the energy crisis worsened with higher, more volatile prices, the spillover effects across markets were slightly lower in 2022.

As mentioned before, the EPD measures the expected proportion of markets in distress, given that one market is in distress. In this regard, the EPD is similar to the CoVaR of Adrian and Brunnermeier (2016) as it

[3] Figure A.2 shows the t-SNE representation for all 14 specifications.

[4] Note that our synthetic prices simulated by the TimeGAN capture the unprecedented increase in energy prices, as shown in Figure A.3. in the Appendix.

**Table 3**
Performance comparison.

| | Discr. score | Accuracy | Precision | Recall | F1-Score | Cohens kappa | ROC AUC | Pred. score | MDD | ACF | Skewness | Kurtosis | t-SNE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| TimeGAN (120, 128, 112) | | | | | | | | | | | | | |
| TimeGAN (90, 128, 112) | | | | | | | | | | | | | |
| TimeGAN (60, 128, 112) | | | | | | | | | | | | | |
| **TimeGAN (30, 128, 112)** | | | | | | | | | | | | | |
| TimeGAN (120, 100, 84) | | | | | | | | | | | | | |
| TimeGAN (90, 100, 84) | | | | | | | | | | | | | |
| **TimeGAN (60, 100, 84)** | | | | | | | | | | | | | |
| **TimeGAN (30, 100, 84)** | | | | | | | | | | | | | |
| TimeGAN (120, 64, 56) | | | | | | | | | | | | | |
| TimeGAN (90, 64, 56) | | | | | | | | | | | | | |
| TimeGAN (60, 64, 56) | | | | | | | | | | | | | |
| TimeGAN (30, 64, 56) | | | | | | | | | | | | | |
| **Copulas** | | | | | | | | | | | | | |
| **Factors** | | | | | | | | | | | | | |

Note: This table reports the metrics performance for 12 TimeGAN specifications. The values in parentheses are in order: sequence length, batch size, and hidden dimensions. We also show copulas estimated using a Gaussian multivariate copula model and factors calculated using a dynamic factor model. We highlight the three best-performing models per metric, with bolder blue indicating the best and lighter blue the third best. According to these metrics, TimeGAN (30,128,112) has the best performance among the models evaluated.

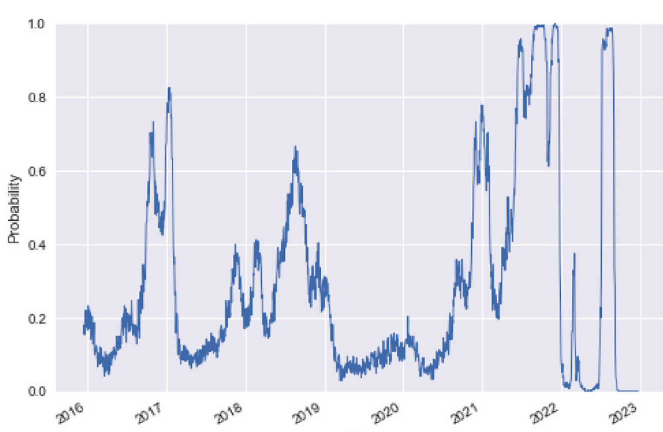



**Fig. 2.** Joint probability of distress ($c = 30\%$)
Note: This figure shows the joint probability of distress, defined as the 95th quantile of prices over the last 250 trading days (approximately one calendar year). We consider the probability that at least eight markets ($c = 30\%$) out of the 25 energy prices are in distress simultaneously.

captures distress spillovers from a single energy series to the broader market. Fig. 3 shows the mean, 25th, and 75th percentiles of the EPD across the 25 energy series in our sample. Between 2016 and 2020, the mean EPD ranged from 20 % to 60 %, with an average of 36 %. During the energy crisis, this indicator highlighted the same periods of systemic risk as the JPD, with the highest EPD recorded in the second half of 2021 and a narrower spread than in the pre-crisis period. In 2022, on average, the EPD returned to pre-crisis levels but still exhibited high volatility, with values surpassing 70 % in August.

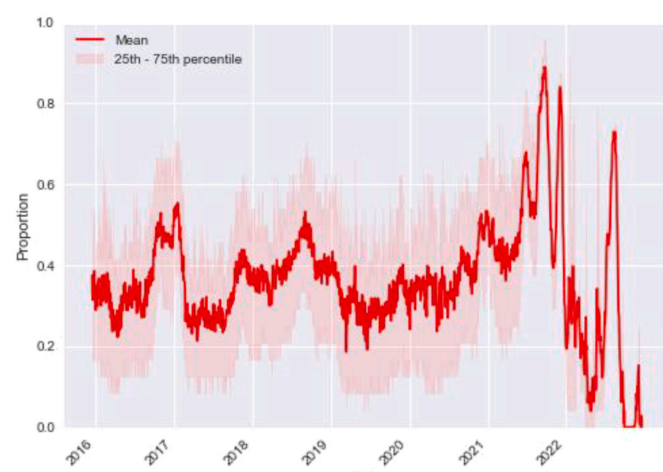



**Fig. 3.** Expected proportion in distress, given one market in distress.
Note: This figure shows the expected proportion of energy markets in distress, given that one (any) market is in distress, averaged across markets. The dark red line is the mean of the expected proportion of energy markets in distress per day, and the red shadow is the 25 % and 75 % percentiles. A market is considered in distress if the simulated price on day $t$ is greater than the 95th quantile of the (real) prices over the last 250 trading days.

The decline in the EPD, reflecting the reduction in spillovers between markets, in 2022, can be related to the measures implemented by the European Union to address high energy prices. These included the Energy Prices Toolbox of October 2021 and the REPowerEU Plan of May 2022. Through these initiatives, the EU aimed to reduce its reliance on Russian fossil fuels by cutting gas consumption, setting regulatory

**Table 4**
Systemic risk assessment of fossil fuels.

| Series | EPD | | | | |
|---|---|---|---|---|---|
| | December 28, 2016 | August 29, 2018 | December 21, 2020 | September 16, 2021 | August 05, 2022 |
| ZEE | 33.33 % | 42.50 % | 49.17 % | 94.17 % | 77.50 % |
| TTF | 44.58 % | 43.75 % | 57.50 % | 99.58 % | 97.92 % |
| API2 | 25.42 % | 47.50 % | 78.33 % | 99.58 % | 2.08 % |
| Brent | 73.33 % | 13.33 % | 0.00 % | 54.17 % | 0.00 % |

Note: This table reports the EPD defined in Equation (5) for the four fossil fuel series in our sample, for five dates when high EPDs (given any market in distress) were recorded.

targets for storage capacity, diversifying energy imports, establishing joint mechanisms for natural gas purchases, and accelerating the expansion of renewable energy generation (European Commission, 2022).

The EPD allows us to identify spillovers from any specific series to the rest of the markets. To better assess changes in spillovers from fossil fuels to other series, Table 4 presents selected dates for the EPD constructed under the scenario in which a fossil fuel price is in distress. These dates were chosen to highlight periods with relatively high EPD values (see Fig. 4).

For the first date, December 2016, the EPD given that ZEE, TTF, or API2 are in distress ranged between 25 % and 45 %, while the EPD given that Brent is in distress reached 73 %. For the following two dates, August 2018 and December 2020, the EPD given the fossil fuels in distress had higher values (between 42 % and 78 %), except for Brent, which had an EPD of 0 % in 2020 due to the residual effect from the pandemic. In September 2021, the EPD given the four fossil fuels reached historically high levels, with the EPD given TTF and API2 exceeding 99 %. By August 2022, the EPD given API2 and Brent had dropped to levels below 3 %, while ZEE and TTF remained at high values but slightly lower than in 2021. These results reflect the central role of natural gas in driving systemic risk in European electricity markets, as most electricity markets in our sample rely more on natural gas than on coal or oil in their generation mix. Summing up, both transnational and national measures aimed at controlling energy prices in the EU appeared to have had an effect on reducing systemic stress in European energy markets.

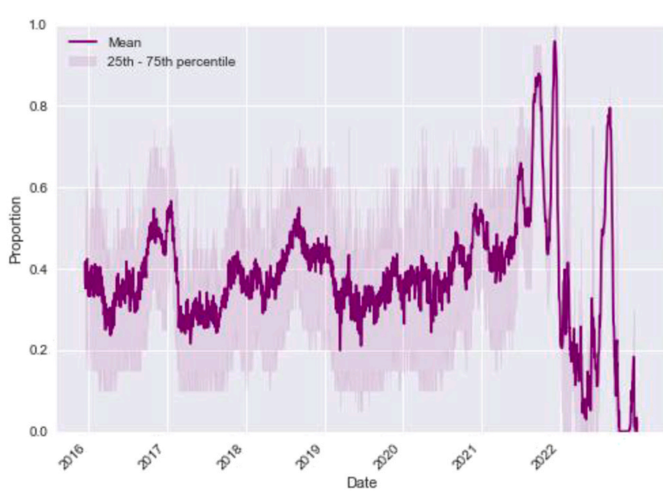



**Fig. 4.** Expected proportion of electricity markets in distress, given one electricity market in distress.
Note: This figure reports the proportion of 21 electricity markets in distress, given that one electricity market is in distress. The dark purple line is the mean of the expected proportion of electricity markets in distress per day, and the purple shadow is the 25 % and 75 % percentiles. A market is considered in distress if the simulated price on day $t$ is greater than the 95th quantile of the (real) prices over the last 250 trading days.

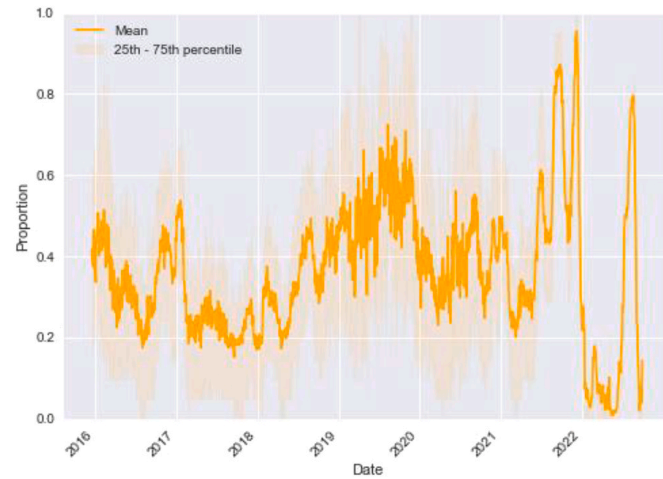



**Fig. 5.** Expected proportion of electricity markets in distress, given one fossil fuel market in distress.
Note: This figure reports the proportion of 21 electricity markets in distress, given that one fossil fuel market is in distress. The dark yellow line is the mean of the expected proportion of electricity markets in distress per day, and the orange shadow is the 25 % and 75 % quantiles. A market is considered in distress if the simulated price on day $t$ is greater than the 95th quantile of the (real) prices over the last 250 trading days.

We also estimate the expected proportion in distress, disaggregated by market. Figs. 4 and 5 present estimates of the EPD for electricity markets, conditional on one electricity market in distress (EPD E|E) and one fossil fuel market in distress (EPD E|F). The EPD E|E follows a pattern similar to that of the EPD calculated for all markets. Specifically, the EPD fluctuated around 40 % from 2016 to 2020, spiked in 2021 to values above 80 %, then decreased at the beginning of 2022, and subsequently showed spikes and higher volatility compared to the pre-crisis period.

For the EPD E|F, the decline in spillovers from fossil fuels to electricity prices during the pandemic is evident in the measure, with a peak of 71 % at the end of 2019, followed by a valley of almost 20 % during the first semester of 2020. The measure spiked again in 2021, with a pattern similar to that of the overall market measure and the EPD E|E. Additionally, the EPD for electricity markets conditional on fossil fuels peaked in August 2022, reaching a level similar to that in 2021, reflecting the continued impact of the energy crisis following the start of the Russia-Ukraine war. On average, the EPD E|F doubled from 2016 to 2020 to 2021, while the EPD E|E rose by 53 %. Thus, our cross-sector systemic risk measure also highlights the significant role of natural gas prices in driving the rise in European electricity prices during 2021.

Although the EPD E|F peaked in August 2022, the measure decreased subsequently and even fell below levels observed during the pandemic. This decline reflects the impact of EU measures to mitigate the energy crisis, as well as national policies to regulate wholesale electricity prices, such as the ‘Iberian Exception’, which imposed a cap on natural gas prices in Spain and Portugal. This policy measure aimed to compensate certain electricity generators that use fossil fuels as inputs, enabling them to make lower-priced bids in the wholesale market. The measure successfully reduced electricity prices, helping to contain inflation and

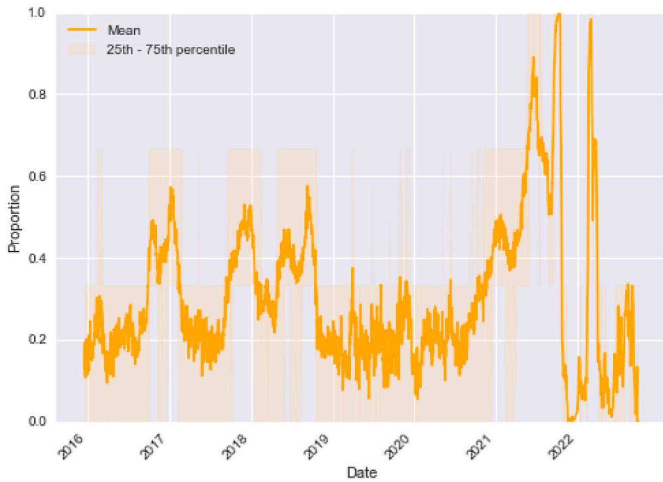



**Fig. 6.** Expected proportion of fossil fuel markets in distress, given one fossil fuel market in distress.

Note: This figure reports the proportion of four fossil fuel markets in distress, given that one fossil fuel market is in distress. The dark yellow line is the mean of the expected proportion in distress per day, and the yellow shadow is the 25 % and 75 % quantiles. A market is considered in distress if the simulated price on day *t* is greater than the 95th quantile of the (real) prices over the last 250 trading days.

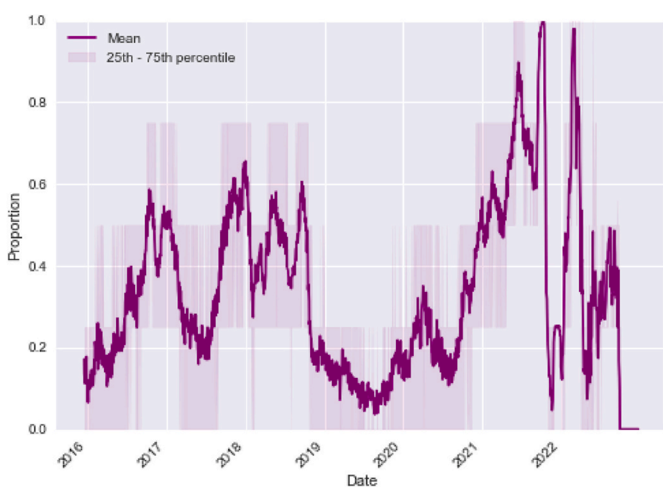



**Fig. 7.** Expected proportion of fossil fuel markets in distress, given one electricity market in distress.

Note: This figure reports the proportion of four fossil fuel markets in distress, given that one electricity market is in distress. The dark purple line is the mean of the expected proportion of fossil fuel markets in distress per day, and the purple shadow is the 25 % and 75 % quantiles. A market is considered in distress if the simulated price on day *t* is greater than the 95th quantile of the (real) prices over the last 250 trading days.

protect consumers' purchasing power. As shown in Figure A.2 in the Appendix, Spanish wholesale electricity prices decreased following the implementation of the measure, while other markets continued to experience inflationary pressures (see also Hidalgo-Pérez et al. (2024) for a causal analysis of the intervention effect on electricity prices). However, it is important to note that this measure created incentives to increase electricity production from fossil fuels, thereby raising demand for natural gas and potentially delaying the energy transition in Spain—effects that this study does not analyze.

Figs. 6 and 7 show the estimates of the EPD for fossil fuel markets, conditional on one fossil fuel market (EPD F|F) or one electricity market (EPD F|E) in distress. The high-risk systemic periods align with those identified in the previous measures, but we observe several heterogeneities when analyzing the spillovers from the different markets.

The EPD F|F averaged 27 % during 2016–2020, but the proportion in distress dropped to below 20 % in 2019 and 2020, accompanied by higher volatility. This shift can be explained by reduced demand for fossil fuels and increased deployment of renewable energy. Specifically, in 2019 and 2020, demand in Europe fell by 3 % and 10 %, respectively, compared with an average annual growth rate of 1 % over the previous five years. During the energy crisis (2021-2020), the EPD F|F averaged 34 %, reaching its highest level in 2021, with several days exceeding 80 %. The EPF F|E exhibits a similar pattern. The measures also peaked at the onset of the Russia-Ukraine war and reached levels above 90 %.

Table 5 presents a regression analysis of our systemic risk measures on various dummy variables representing different sub-periods within our sample. The sub-periods assessed are the third and fourth quarters of 2021 and the first and second quarters of 2022. These dates correspond to the European energy crisis, when our systemic risk indicators reached their highest levels. For all the measures, aggregated (JPD and EPD) and sectoral (EPD E|E, E|F, F|F, F|E), systemic risk is higher in the third quarter of 2021 than in the other quarters, being the only period where the effect is statistically significant and positive for all indicators. In 2021 Q4, the aggregated and EPD E|E and E|F measures are positive but have smaller values, and are negative in the two quarters of 2022. For EPD F|F and F|E, 2021 Q4 is negative, while 2022 Q1 for EPD F|F remained unchanged, and 2022 Q2 is negative again. Overall, electricity markets experienced greater systemic distress in Q3 2021 than in the final months of 2021 and the first semester of 2022, despite electricity prices reaching record highs in the latter period. The commitment to intervene in electricity and natural gas markets appears to have significantly reduced systemic stress in European electricity markets.

### 5.3. *Robustness check*

As a robustness check, we estimated the indicators by simulating prices with the same specification (30 days as the sequence length, 120 as the batch size, and 112 hidden dimensions) and with smaller samples to see whether they changed only during the energy crisis or across all time. Fig. 8 shows the JPD for a subsample of data from 2015 to 2021 (Panel A) and from 2015 to 2020 (Panel B). Both subsamples show a pattern similar to the corresponding dates in the measure estimated from the full sample. However, as expected, when part of the energy crisis is not included (Panel A), the peaks and troughs are more pronounced (e.g., the peak in the measure at the beginning of 2017 with the subsample exceeds 90 %, while the same peak with the full sample reaches 82 %), as well as lower volatility in the measure. This behavior is even more pronounced when no part of the energy crisis is included (Panel B). This pattern suggests that removing the historically high prices and volatility leads to lower average estimates, with lower troughs and higher peaks.

As in the case of the JPD, the aggregated EPD for both subsamples (Fig. 9) exhibits lower levels and volatility, as removing the crisis from the price simulation underestimates the true volatility; yet, the peaks are very similar to those estimated with the complete sample. In any case, the measure estimated with the simulation of prices from the subsamples captures the same episodes of systemic risk as the simulation including

**Table 5**
Time effects on systemic risk indicators.

| Systemic risk measure | JPD - k = 30 % | EPD | EPD E\|E | EPD E\|F | EPD F\|F | EPD F\|E |
|---|---|---|---|---|---|---|
| Intercept | 0.2410*** | 0.3513*** | 0.3686*** | 0.3626*** | 0.2917*** | 0.3059*** |
| | (0.005) | (0.003) | (0.003) | (0.003) | (0.005) | (0.005) |
| 2021 Q3 | 0.5165*** | 0.1906*** | 0.1885*** | 0.1780*** | 0.1481*** | 0.2263*** |
| | (0.019) | (0.011) | (0.011) | (0.012) | (0.016) | (0.018) |
| 2021 Q4 | 0.0772** | 0.0293* | 0.0603*** | 0.0751*** | −0.2122*** | −0.1849*** |
| | (0.031) | (0.018) | (0.018) | (0.020) | (0.026) | (0.029) |
| 2022 Q1 | −0.6685*** | −0.2775*** | −0.3136*** | −0.4364*** | −0.0287 | 0.0739*** |
| | (0.029) | (0.018) | (0.018) | (0.020) | (0.026) | (0.029) |
| 2022 Q2 | −0.7297*** | −0.3827*** | −0.4095*** | −0.4710*** | −0.3479*** | −0.2738*** |
| | (0.029) | (0.018) | (0.018) | (0.020) | (0.026) | (0.029) |

Note: This table shows the time effects on the estimated systemic risk indicators for the third and fourth quarters of 2021 and the first and second quarters of 2022. JPD stands for joint probability of distress, defined as the 95th quantile of prices over the last 250 trading days. We consider the probability that at least eight markets ($c$ = 30%) out of the 25 energy prices are in distress simultaneously. EPD stands for expected proportion in distress. EPD E|E stands for the expected proportion of 21 electricity markets in distress, given one electricity market in distress. EPD E|F stands for the expected proportion of 21 electricity markets in distress, given one fossil fuel market in distress. EPD F|F stands for the expected proportion of four fossil fuel markets in distress, given one fossil fuel market in distress. EPD F|E stands for the expected proportion of four fossil fuel markets in distress, given one electricity market in distress. ***, **, and * indicate statistical significance at 99 %, 95 %, and 90 % confidence levels, respectively.

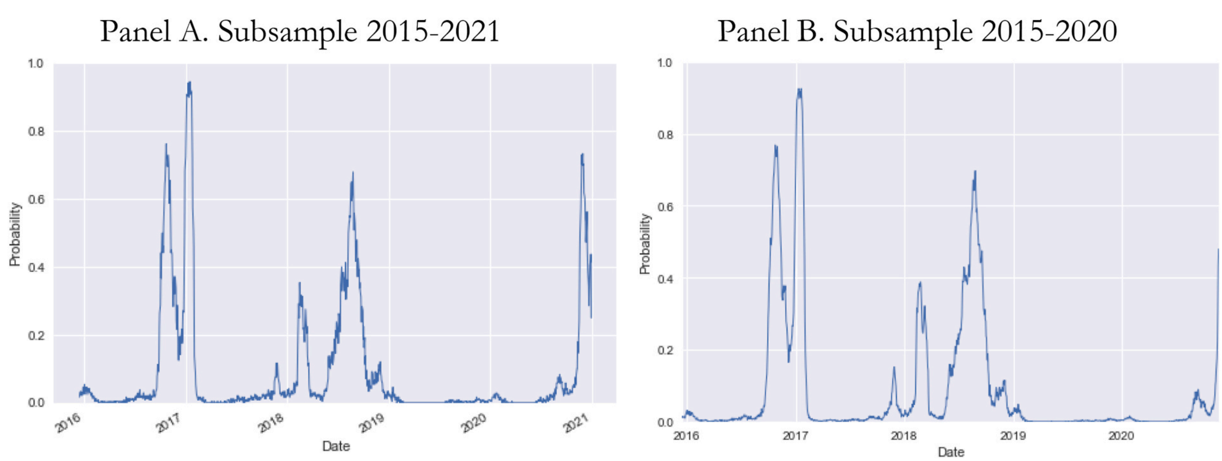



**Fig. 8.** Joint probability of distress ($\boldsymbol{c}$ = **30%**) – segmented samples.
Note: This figure shows the joint probability of distress, where distress is defined using the 95th quantile. We consider the probability that at least eight markets ($c$ = 30%) out of the 25 energy prices are in distress simultaneously.

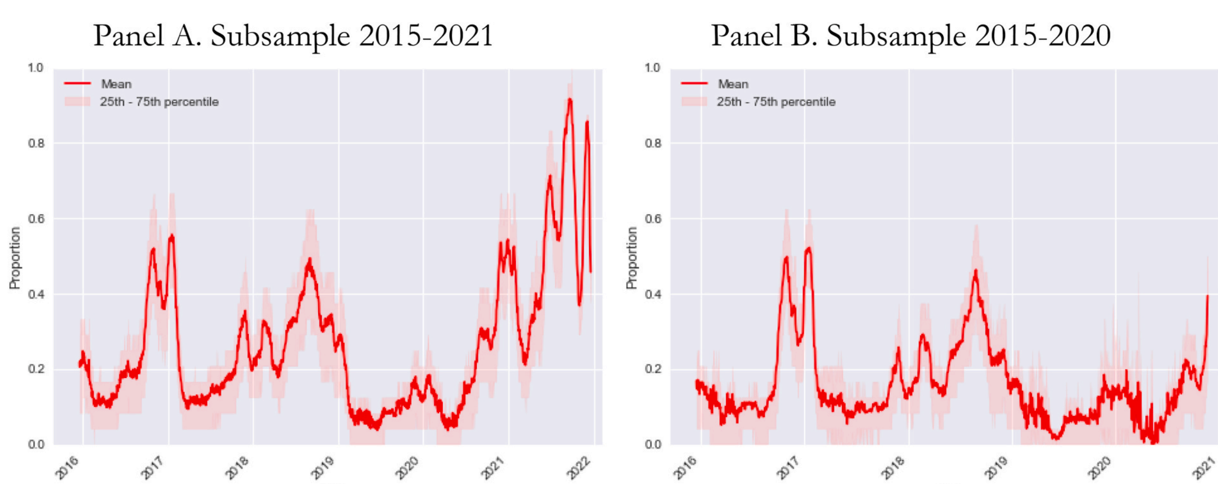



**Fig. 9.** Expected proportion in distress, given one market in distress - segmented samples.
Note: This figure shows the expected proportion of energy markets in distress, given that one (any) market is in distress, averaged across markets. The dark red line is the mean of the expected proportion of energy markets in distress per day, and the red shadow is the 25 % and 75 % percentiles. A market is considered in distress if the simulated price on day $t$ is greater than the 95th quantile of the (real) prices over the last 250 days.

the crisis.

## 6. Conclusions and policy implications

Our study makes two significant contributions to the energy economics literature. First, we pioneer an integrative approach to analyzing systemic risk scenarios within electricity markets, encompassing 25 energy markets—including oil, natural gas, coal, and 21 electricity markets. Second, we introduce Time Series Generative Adversarial Networks (TimeGANs) to the field of systemic risk, demonstrating their utility in real-time tracking of market resilience.

By employing the TimeGAN model, which accounts for both linear and nonlinear correlations and temporal dependencies, we generated over 1000 simulations of our energy price dataset. The synthetic data was then used to estimate indicators of systemic risk. Unlike traditional methods that require specifying a density function, Generative Adversarial Networks focus on learning a tractable sample generation process. Our findings include synthetic data optimized to best fit our real-world dataset, as well as estimates of systemic risk, both aggregated across all markets and disaggregated by sector—electricity versus fossil fuels.

Additionally, we examined the temporal evolution of these systemic risk indicators, providing insights into the dynamics of risk during the recent European energy crisis and guidance for policymakers. In short, JPD and EPD systemic risk indicators serve as diagnostic and monitoring tools to detect systemic vulnerabilities and inform targeted interventions. As EPD can be estimated for the whole market, across sectors, and within sectors, its granularity allows policymakers to target specific markets or sectors with the highest EPD values for focused stress testing and preventive action. Conversely, if the EPD associated with a particular market is low (closer to zero), it implies that distress in that market is relatively contained. Policymakers could interpret low EPD as evidence of effective regulatory firewalls or sufficient resilience within the broader market structure.

Our results reveal that energy markets, particularly power markets, experienced greater systemic distress in the third quarter of 2021 compared to the last months of 2021 and the first semester of 2022, despite record-high electricity prices in the latter period. The commitment to policy interventions in the electricity and natural gas markets appears to have notably reduced systemic stress in European electricity markets. However, this mitigating effect did not fully extend to the fossil fuel markets, where systemic risk peaked in the first quarter of 2022, reaching levels similar to those in 2021 Q3. This indicates that the supply shock from the onset of the Russia-Ukraine conflict significantly impacted systemic risk in fossil fuel markets, despite regulatory efforts by the EU and national policymakers.

From a policy perspective, these findings highlight the trade-offs policymakers face between short-term stabilization and long-term sustainability goals. Policymakers face a complex challenge: managing immediate financial distress and high consumer prices, as indicated by elevated JPD and EPD values, often requires interventions that can conflict with climate objectives. The European Union's broader initiatives, such as the REPowerEU Plan, aimed to balance these objectives by cutting gas consumption, diversifying energy imports, and accelerating renewable energy deployment. Yet, the specific outcome of the "Iberian Exception" exemplifies a policy paradox: while such measures effectively stabilized prices in the short term in Spain and Portugal, they may also have reinforced the economic viability of fossil fuels, thereby slowing the energy transition.

Our indicators assess systemic risk in the short term, focusing on the right tail of the distribution of energy prices. Specifically, our model is tailored to situations where prices are high enough to threaten energy security. However, our analysis is not designed to address the risks renewable energy sources face when prices remain persistently low over the medium to long term, a phenomenon related to the 'missing money' problem. These risks cannot be assessed by focusing on daily price variations or the tails of the price distribution at such frequency. Instead, they stem from the average price level and the potential for a project's cash flow to be insufficient over the long term to recover its initial investment.

Yet, our models pave the way for a new generation of risk modeling in energy markets, taking an integrative approach and leveraging recent advances in artificial intelligence. Our approach to estimating systemic risk in electricity markets can serve as a valuable input for policymakers considering establishing risk regulation for electricity markets, similar to the Basel or Solvency frameworks used for banks and insurance companies, given that EU commodity companies are not currently subject to conduct and prudential regulations. As the European Commission (2024) moves toward a common trading rulebook for spot and derivatives markets, enabling the supervision of trading activities and the establishment of financial position limits, our findings highlitht the importance of having hedging instruments that allow countries or electricity bidding zones to hedge power trades between them, which will be even more critical as renewable generation increases and the European power system becomes more dependent on weather factors and climate variations.

Future extensions of our work include analyzing how weather, climate change, renewable generation, or policies affect systemic risk. Future work may also employ newer techniques such as CTGAN and DGAN; these methods seek to overcome the limitations of TimeGAN in modeling cross-sequence dependencies or in combining short-term and long-term temporal dynamics beyond the chosen sequence length (Claeys et al., 2024; Lu et al., 2022).

All in all, our results highlight both the effectiveness of coordination and policy commitment at the European level in mitigating systemic risk and the threats to energy security arising from fossil fuel dependence. The findings call for policies that balance crisis management with structural transformation, ensuring that energy market stability evolves in parallel with climate and sustainability goals. Unlike previous policy discussions on this topic, our models provide an effective quantitative framework for measuring and assessing these system risk dynamics.

## CRediT authorship contribution statement

**Santiago Bohórquez Correa:** Writing – review & editing, Writing – original draft, Software, Investigation. **Stephanía Mosquera-López:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Jorge M. Uribe:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jorge M. Uribe reports financial support was provided by Government of Catalonia Agency for Administration of University and Research Grants. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix

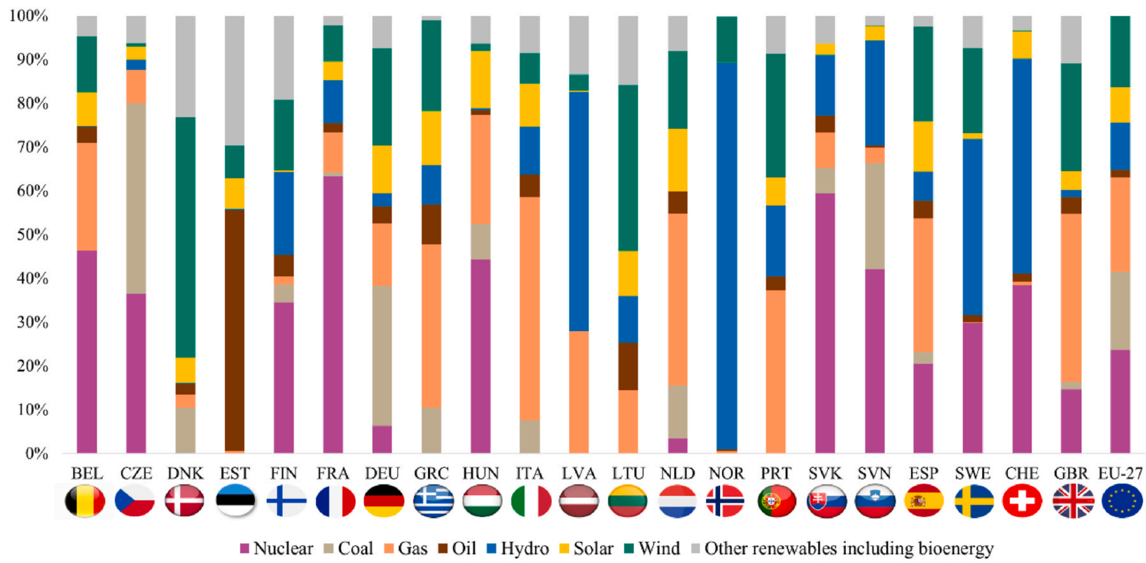



**Fig. A.1.** Share of electricity generation by source in 2022
Source: own elaboration with data from ourworldindata.org.

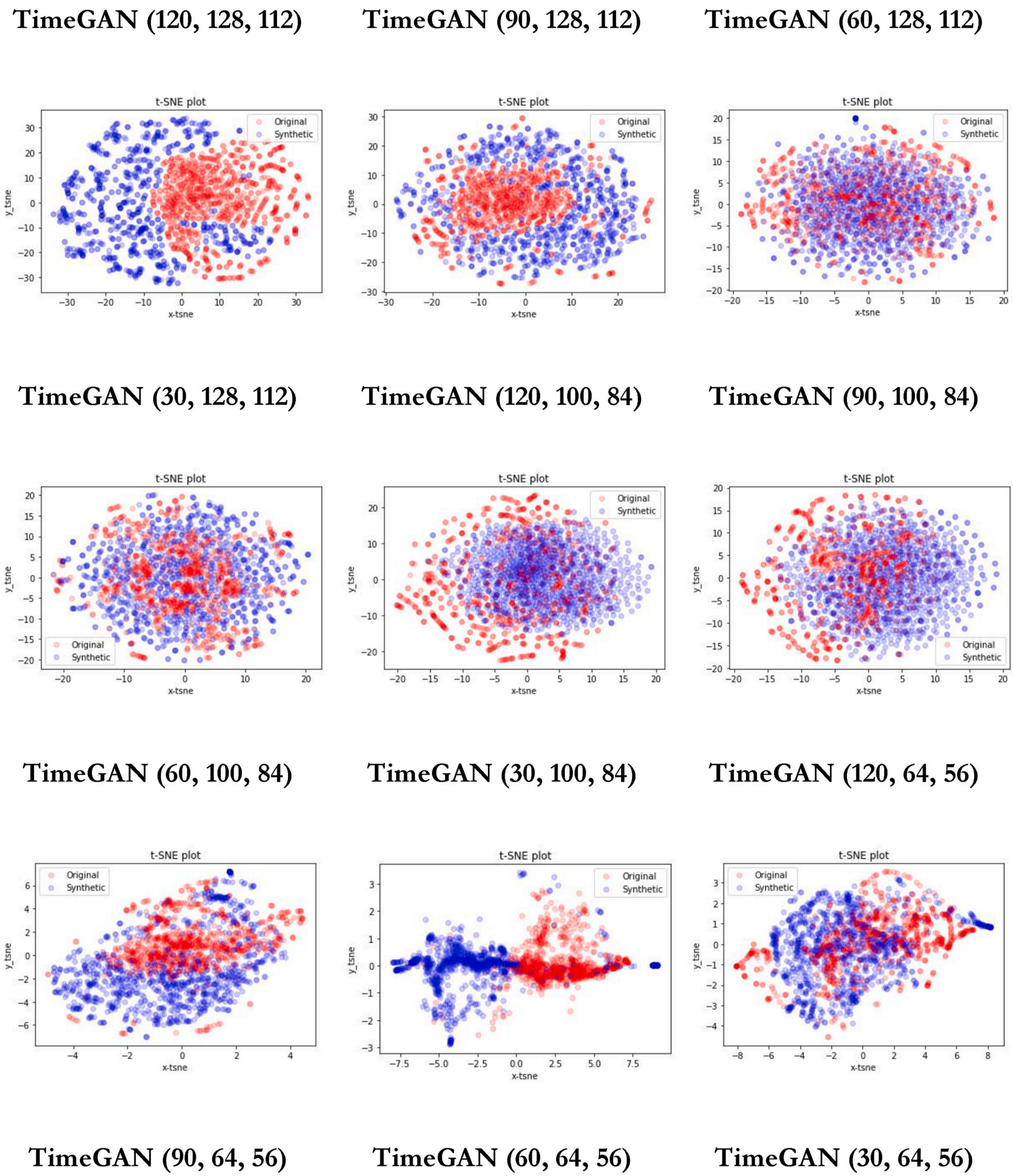
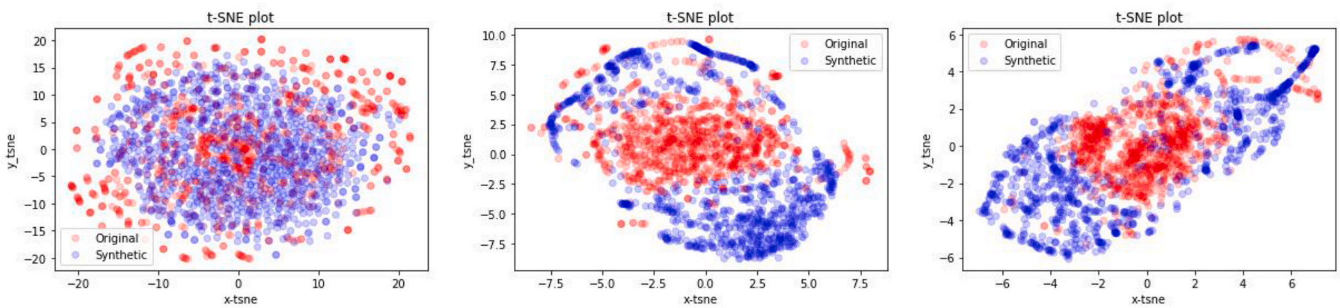



**Fig. A.2.** . t-SNE analysis.

Note: This figure contains the t-distributed stochastic neighbor embedding (t-SNE) data dimensionality reduction visualization for the 12 TimeGAN specifications (Yoon et al., 2019). The red dots correspond to the original data, and the blue dots correspond to the synthetic data. This visual test was done for the copulas and factor models using the original t-SNE (van der Maaten and Hinton, 2008).




**Copulas** **Factors**

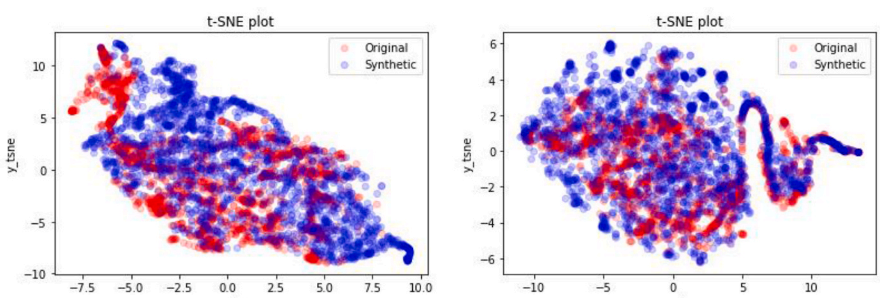



**Fig. A.2.** (*continued*).

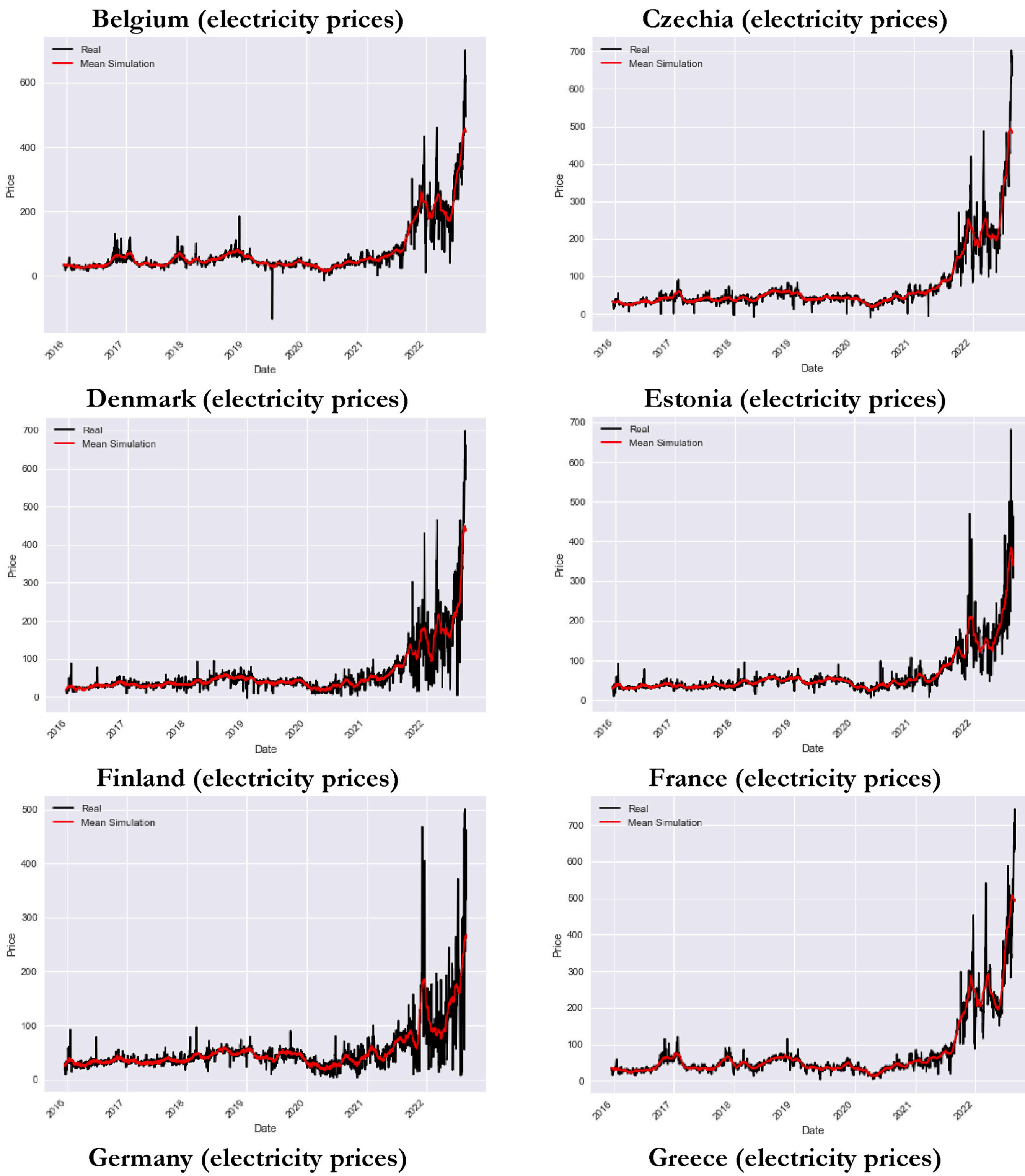
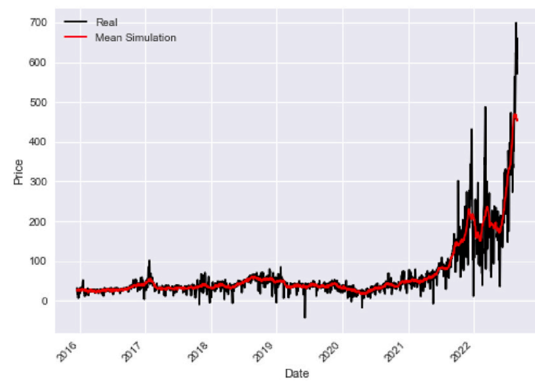
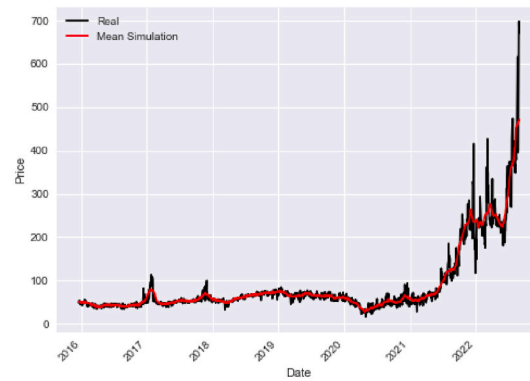


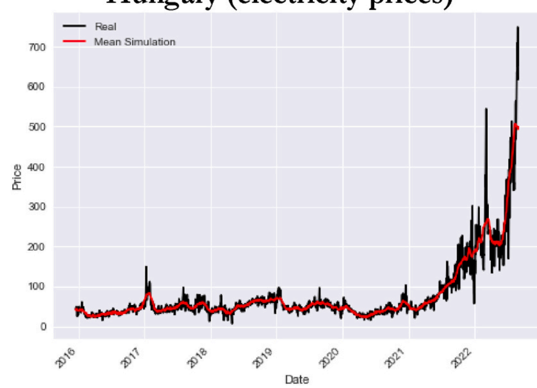

**Fig. A.3.** (Real) energy prices vs median of simulated energy prices.
Note: The black line corresponds to the real prices observed in each market, while the red line is the median value of the 1080 simulation values or synthetic prices.



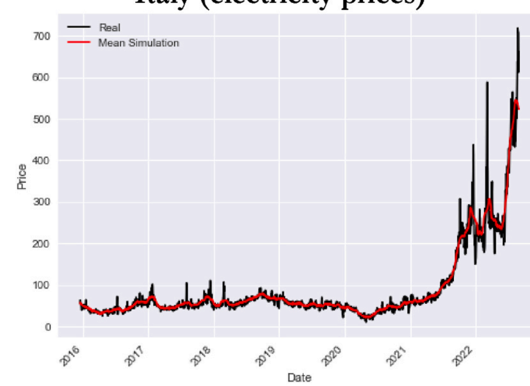

Hungary (electricity prices)



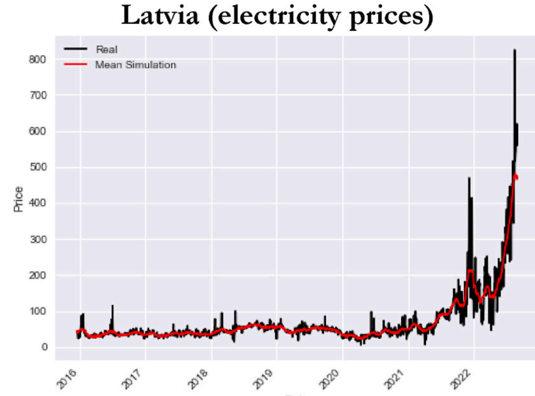

Italy (electricity prices)



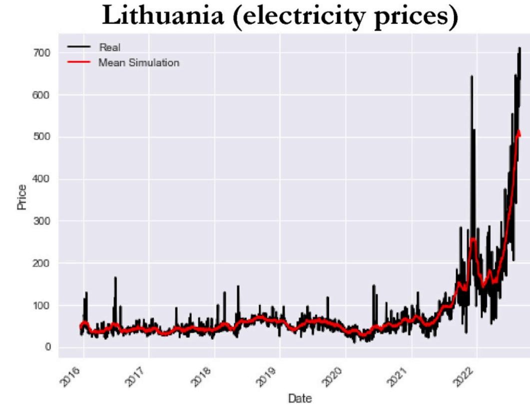

Latvia (electricity prices)



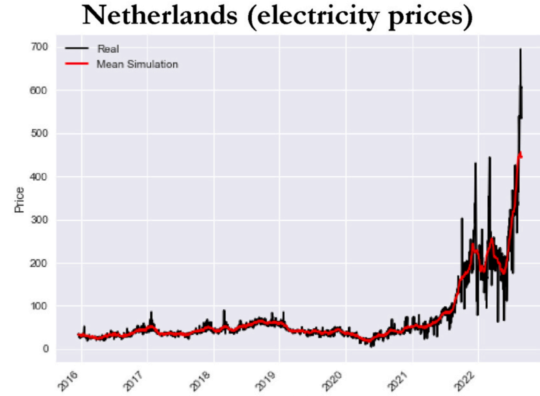

Lithuania (electricity prices)



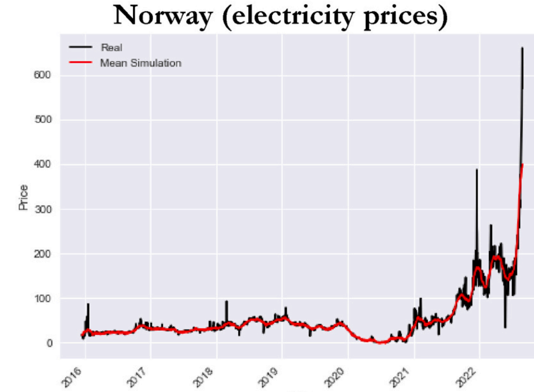

Netherlands (electricity prices)




Norway (electricity prices)




Portugal (electricity prices)




Slovakia (electricity prices)

**Fig. A.3.** (*continued*).

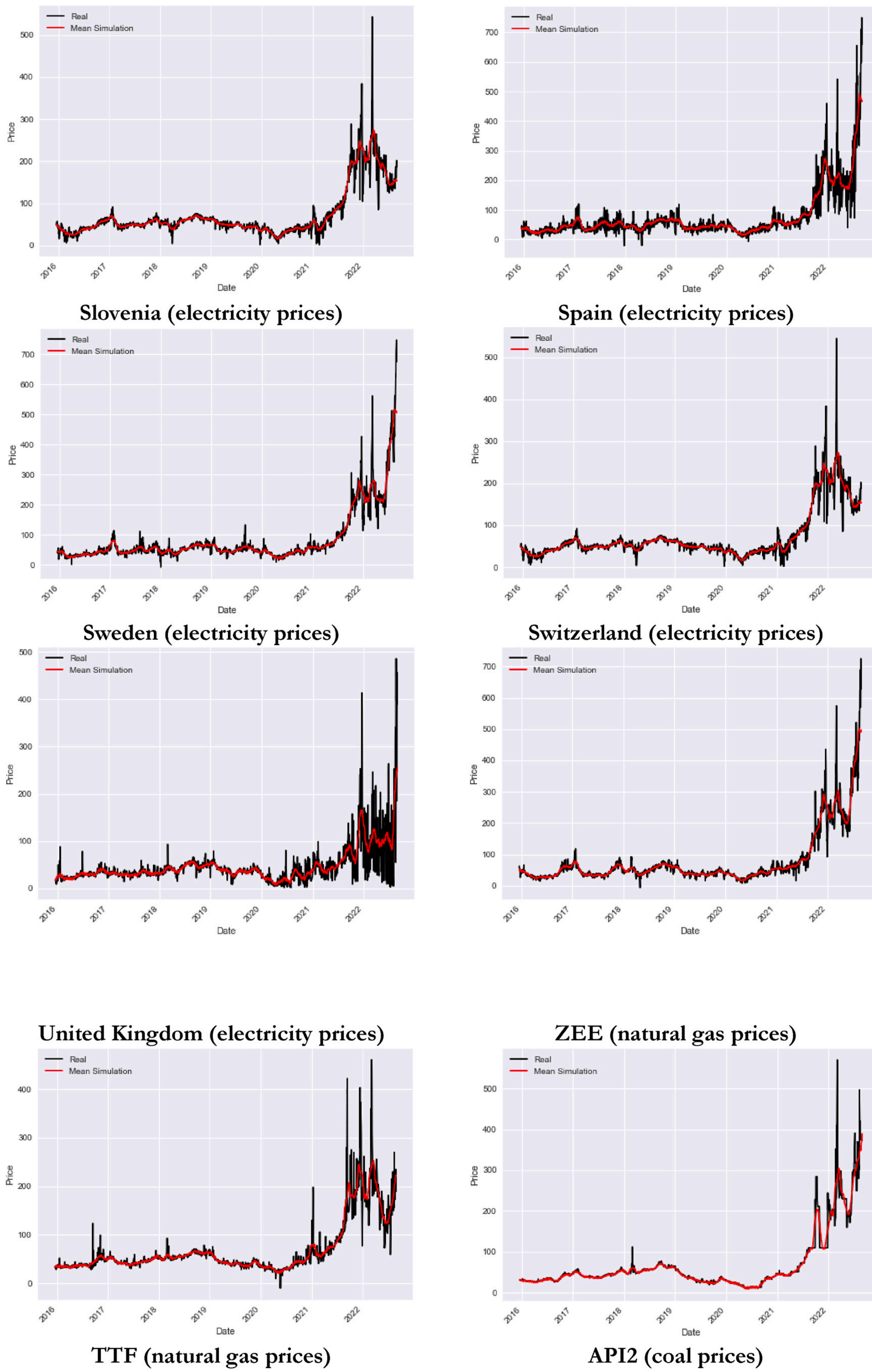
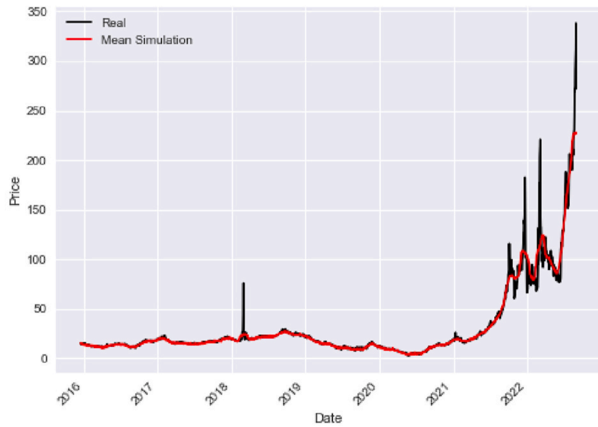
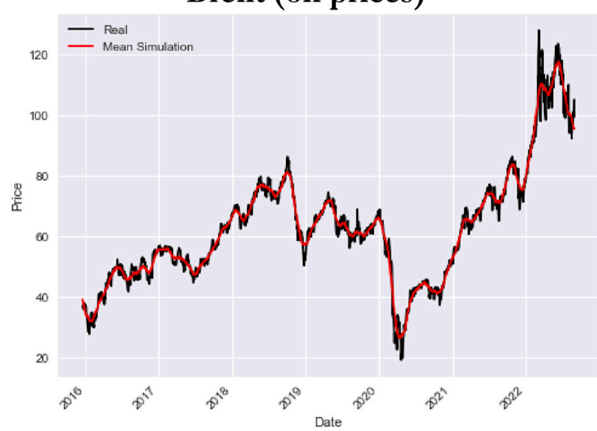



**Fig. A.3.** (*continued*).





**Brent (oil prices)**




Note: The black line corresponds to the real prices observed in each market, while the red line is the median value of the 1,080 simulation values or synthetic prices.

**Fig. A.3.** (*continued*).

## Data availability

The authors do not have permission to share data.

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