**Master Thesis Financial Economics**

The influence of a growing share of renewable electricity generation on Dutch day-ahead electricity prices and their volatility

*A study over periods of fallen demand and supply chain disruptions*

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**Abstract**

This paper investigates the influence of renewable electricity generation on day-ahead electricity prices and their volatility in the Netherlands over the period 2018-2022. This study defines three sample periods, representing falling demand, rising demand, and supply chain distortions, and compares the outcomes against a base case. The study employs ARMA and ARMAX models, and finds evidence for the merit order effect. The results indicate that renewable electricity generation does not significantly influence weekly electricity price volatility.


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# 1. Introduction

Renewable energy is among the most discussed topics in today's world. As documented in the Paris Climate Agreement, all United Nations countries have agreed upon the overarching goal of keeping "the increase in the global average temperature to well below two degrees celsius above pre-industrial levels" and pursuing efforts "to limit the temperature increase to one-and-a-half degrees above pre-industrial levels" (United Nations Climate Change, n.d.). One of the key changes needed is in the way we produce our energy since we need to shift away from fossil fuels to renewables to achieve the CO2 reductions needed. As we make this shift towards renewables, we are fundamentally reshaping the energy market. This stems from the characteristic differences between renewable and fossil energy sources in terms of price and flexibility amongst others. In the wake of the COVID-19 pandemic, the European energy market, and the world market to a lesser extent, has been confronted by the outbreak of the war between Russia and Ukraine. Electricity prices skyrocketed to the point where the Dutch government had to introduce a multitude of new schemes to provide liquidity to consumers and businesses. As we are continuing the path toward a higher share of renewables, and large shocks toward the energy systems are likely to occur in the future, examining the effect of renewables on electricity prices and volatility in turbulent times is highly relevant.

There is an extensive body of research on electricity prices and their volatility. The electricity market fundamentally works like other markets, though the merit order, a sequence in which power plants contribute energy to the market, determines power prices. The cheapest offer made by the power station with the smallest running costs serves as the starting point. Renewable power stations such as wind turbines and photovoltaic installations (solar power) have the lowest operating costs. Their introduction lowers the entrance price and pushes conventional producers down the merit order. The merit order effect describes the drop in the level of electricity prices with the addition of renewable electricity to the grid and is widely found in the literature (Gelabert, Labandeira and Linares, 2011; Woo, Horowit., Moore and Pacheco, 2011; Jónsson, Pinson, and Madsen, 2010; Ketterer, 2014; Forrest & MacGill, 2013; Brancucci Martinez-Anido et al., 2016, among others). Ketterer (2014) finds that the negative impact of wind power on electricity prices is more substantial during periods of high demand compared to low demand. Several studies also find the merit order effect to reduce over time, possibly due to the increasing share of solar PV feed-in (Sensfuß, 2011; Gelabert et al., 2011).

For the Netherlands, Mulder and Scholtens (2013) find that gas prices are the key factor positively influencing electricity prices. They too find the merit order effect. However, despite the strong growth in installed wind capacity, they have not found a more substantial effect over time. This result may have changed with the strong growth in installed renewable capacity over the last years.

Spot price volatility is found higher during periods of high demand and vice versa for low demand (Knittel & Roberts, 2005; Bessembinder & Lemmon, 2002; Bowden & Payne, 2008). This finding is a result of the convex marginal cost structure of electricity prices. Further, in periods of high demand, additional generators with greater marginal costs are brought online to match demand, resulting in higher price volatility (Mwampashi et al., 2021). Ketterer (2014) and Rintämaki, Siddiqui and Salo (2017) find opposite effects for wind- and solar power on price volatility, where solar would decrease volatility during peak hours. Previous literature has not found conclusive evidence of the impact of renewables on price volatility.

This paper aims to study the beforementioned effects during times of fallen demand and supply chain distortions. Consequently, we formulate the research question as "How does the influence of a growing share of renewable electricity generation on Dutch day-ahead electricity prices and their volatility evolve over periods of low demand and supply chain disruptions?". We analyze this question by modeling the effect of renewables on prices and their volatility over the past five years. We establish 2018 and 2019 as our base case and compare periods of fallen demand, risen demand, and supply chain distortions against it. A base case consisting of two years is relatively short, but is chosen in this study such that it represents an up-to-date period of renewable electricity generation. With an annual growth rate of renewable energy production in the Netherlands of between twelve and forty-five percent over the period 2017 – 2020 (CBS, 2023), taking a recent base case can offer interesting insights. We specifically define the time frame of the COVID-19 pandemic as spanning the years 2020 and 2021. Subsequently, we separate this into two distinct phases: a period characterized by decreased demand, followed by a period of recovery and rising demand. Additionally, the Russian-Ukrainian conflict is designated to 2022. Despite the fact that Russian forces initiated an attack on Ukraine in February 2022, rumors regarding potential conflicts between the two nations had been circulating prior to this event. We assume that market players were able to anticipate the effects that this conflict would have on the energy supply chain, thereby necessitating the inclusion of the entirety of the year 2022 within the study period. To our knowledge, no previous research has investigated the impact of these events on the Netherlands in a single study. With a share of 25% in the 2021 energy grid coming from wind and solar power (CBS, 2023), looking into the influence these renewable energy sources have on prices in the Netherlands is highly relevant. The vulnerability of the global energy trade and the unpredictability of fossil fuel prices have raised concerns about the energy system's ability to withstand unforeseen shocks such as pandemics and geopolitical conflicts. Understanding the effects of such disruptions on the transition to low-carbon energy systems is crucial for developing context for legislation to address these effects. This study can yield valuable insights for policymakers, especially in the event of new infection waves, a new pandemic, or further supply chain disruptions. Additionally, it can assist market participants in explicitly considering changes in the global health or political landscape while forecasting appropriate responses to energy price shocks.

We find that renewable electricity generation is significant in explaining price movements, confirming the merit order effect. Further, we find that during the rebound period right after the COVID-19 pandemic and the period of war, the addition of renewables in the grid impacts prices significantly more compared to our base case. It is well established that during periods of high demand, renewables influence prices more significantly. We add that in periods of low supply, this merit order effect is more pronounced. Though our results suggest the likeliness of renewables becoming more significant in explaining volatility over our samples, we cannot statistically prove this.

The remainder of this paper is organized as follows. In section 2, we review previous literature and provide context on the electricity market and the events that occurred. In section 3, we discuss the data we use. Section 4 presents our model and our data’s properties. Section 5 shows the results of our analyses and extensions to our models. Section 6 presents our conclusions and implications. Finally, in section 7, we discuss this paper’s limitations and provide directions for future research.

## 2. Theoretical background

### 2.1 The energy market

An extensive network of powerlines, consumers and producers ensure electricity is available at all times. A well-functioning electricity market is the foundation of this system. The following section explains some basic characteristics of the Dutch energy market.

### *2.1.1 Overview of the Dutch energy market*

The electricity market in the Netherlands operates similarly to other markets, in which producers can make their electricity available on a market platform, and consumers can acquire it for delivery within specific timeframes. Participants in the market, including buyers and sellers, are granted three fundamental freedoms (TenneT, n.d.):
The *freedom to dispatch* entails that generators and consumers have the right to produce or consume their preferred amount of electricity within the limits of their connection agreement. The *freedom of transaction* enables market parties to enter into any form of contractual agreements regarding their demand and supply. Lastly, with the *freedom of connectivity* all resources can connect into the grid in a non-discriminatory manner.

Though the market fundamentally works like any other, electricity is a unique good because of three particular characteristics (TenneT, n.d.). First, since electricity is difficult to store presently, its supply and demand must always be balanced. Therefore, electricity has a fluctuating market value throughout the day. In the longer term, electricity prices are also strongly dependent on fuel costs (e.g., natural gas) and CO2 prices. Moreover, market participation is free, but the transmission capacity is limited. Transmission System Operators ensure that transmission lines are operated within safe parameters to prevent the occurrence of cascading blackouts. As a result, the market value of electricity can vary among different load frequency control regions, such as in the case of the Netherlands. Lastly, demand, generation, and location must always match, but this becomes difficult when we are integrating more variable and decentral renewables into the grid. Therefore, flexibility in both time and location can be of great value.

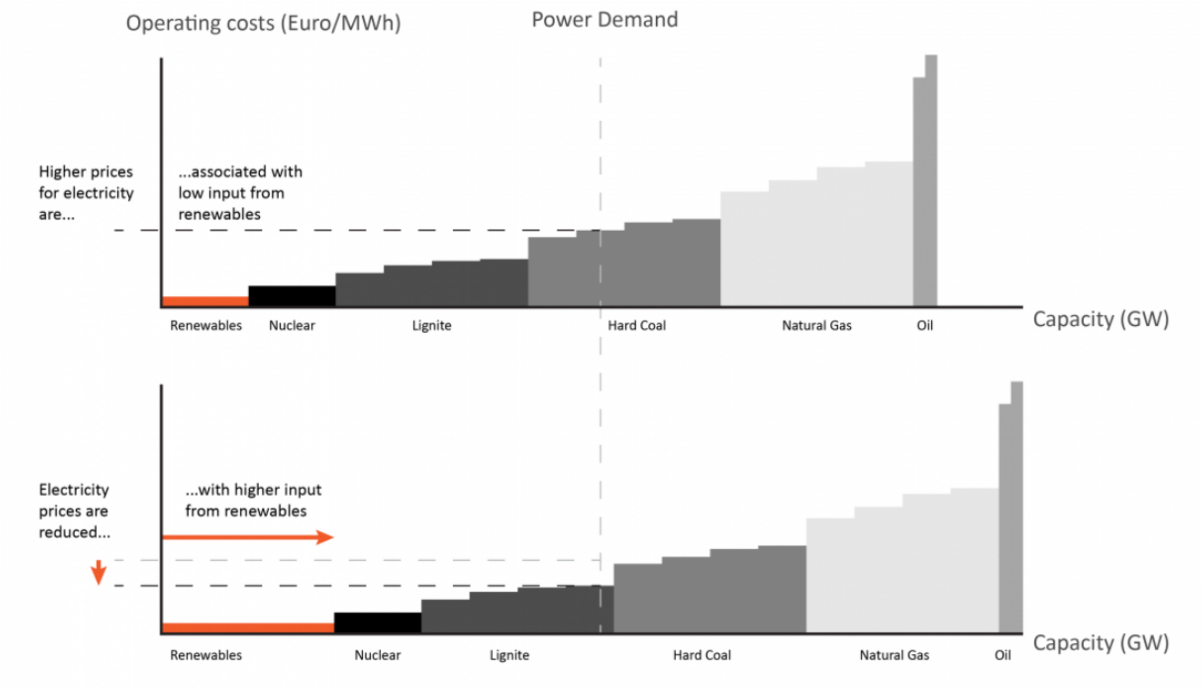
### *2.1.2 Electricity prices and the merit-order effect*

The electricity generated by renewable energy sources impacts the market and its prices.

The merit order determines the power price. It is the sequence in which power plants contribute to the market. The cheapest offer made by the power station with the smallest running costs serves as the starting point. Power from renewable installations (wind turbines, photovoltaic installations) sells on the exchange too. These suppliers have the lowest operating costs, since they do not need a power source (fuel) or much manpower. In turn, they lower the entrance price and push more expensive, conventional, producers down the merit order as shown in Figure 1.

As in other markets, the intersection of power demand and supply determines the clearing price and clearing volume. All electricity generators participating in the market will receive this clearing price for the electricity they produce for the grid.

Figure 1: Illustration of Electricity Price Fluctuations due to the Merit Order Effect




Source: Clean Energy Wire CLEW, 2016

The merit order explains the mechanism which determines the market price. In the energy market, the merit order effect describes the lowering of power prices at the electricity exchange due to an increased supply of renewable energies. The rise in renewable electricity generation displaces marginal power plants from the market, pushing the electricity supply curve to the right and subsequently decreasing electricity prices.

*The merit order effect*

Gelabert et al. (2011) found a significant drop in the level of electricity prices in Spain, as also found by Woo et al. (2011) for Texas, for an increasing share of wind power. This merit-order effect from wind power is later confirmed by Jónsson et al., (2010), Ketterer (2014), Forrest and MacGill (2013), and Brancucci Martinez-Anido et al. (2016) among others. Ketterer (2014) adds that the negative impact on electricity prices from wind power is more substantial with higher levels of demand. Moreover, the paper suggests that the merit-order effect reduces over time, a finding that Sensfuß (2011) finds for Germany. This can partly be explained by the specific market design of a country's electricity market.

Würzburg et al. (2013) have conducted a study on the effect of renewables for a number of European countries. The study finds that the smallest merit-order effects exist in large European markets (such as Germany, Spain), in contrast to much higher price effects in small markets (Netherlands, Denmark, Ireland). Accounting for differences in market size makes for more similar effects. This is especially the case for electricity systems with sizeable fossil capacities, where fossil plants are still the price-setting marginal plant, at least during demand peaks, which is the case for the Netherlands.

For the Netherlands, Mulder and Scholtens (2013) find that gas prices are the key factor positively influencing electricity prices. They too find the merit order effect. However, despite the strong growth in installed wind capacity, they have not found a more substantial effect over time, contradicting the results for Spain of Gelabert et al. (2011) and other beforementioned studies. Moreover, the study finds no significant relation looking at solar impact on electricity prices. This is likely due to its small share of electricity generation in the grid. The findings suggest that the intersection of the demand and supply curves in the Dutch market is hardly influenced by the merit-order effect. A note here is that these results may differ when differentiating between peak hours, when the supply curve is steeper than on average during the day. Moreover, this result might have changed over the last years, with the steep increase in renewable energy production in the Netherlands.

Dillig et al (2016) finds the merit-order effect looking at renewables combined (solar and wind as one). The paper suggests that solar power generation is also responsible for lowering electricity prices in Germany. Kyritsis, Andersson and Serletis (2017) add that solar power generation reduces the probability of electricity price spikes while, on the other hand, wind power introduces electricity price spikes.

There are many more factors influencing electricity prices. Among others, Bulavskaya and Reynes (2018) suggest that renewable technologies typically require higher investments per unit of output than fossil fuel technologies, which can increase electricity prices. The relative increase in the electricity price strongly depends on the projected costs of the technologies, giving a high uncertainty range. Moreover, Brancucci Martinez-Anido, C., et al. (2016) in their paper find perfect versus operational forecasting to influence their findings as well.

### *2.1.3 Renewable energy*

The International Energy Agency (IEA) defines renewable energy as “energy derived from natural processes that are replenished at a faster rate than they are consumed”, and mentions solar, wind, geothermal, hydro and biomass as examples of renewable energy (Harjanne and Korhonen, 2019). The European Union includes wind, solar, hydro and tidal power, geothermal energy, ambient heat from heat pumps, biofuels and the renewable part of waste as renewable energy in its statistical accounting (Eurostat, 2022).

Countries all over the world have seen an increase in the share of renewable energy production, mainly due to the widely granted feed-in tariffs (Senfuβ, Ragwitz and Genoese 2008). These renewable energy sources barely use any costly inputs (fuel), which makes the marginal costs minimal (or even nonexistent).

### *2.1.4 Volatility*

From theory and previous literature, we expect solar generation to exhibit lower variability than wind power generation. Consequently, due to their flexibility, power plants adjust their production for remaining demand efficiently. This way solar power generation manages to reduce electricity price volatility. Wind power has a greater generating capacity than solar and is expected to exhibit more variable production. As a consequence, the integration of large quantities of wind power into the system may result in increased price volatility due to its high generation variability (found by Kyritsis et al, 2017).

Knittel and Roberts (2005) and Bessembinder and Lemmon (2002) find a positive skew contained in power spot prices that is larger (smaller) during periods of high (low) demand variability. A similar pattern exists for the volatility of spot prices, which is found higher (lower) during periods of high (low) demand. The finding that electricity price volatility tends to rise more so with positive shocks than negative shocks is a result of their convex marginal costs, a finding later confirmed by Bowden and Payne (2008), Ketterer (2014), and Mwampashi et al. (2021). Mwampashi et al. (2021) add that positive shocks may represent unanticipated increases in demand. When coupled with convex marginal costs, this in the short run makes for additional generators with greater marginal costs to come online to match demand, resulting in higher price volatility.

Brancucci Martinez-Anido et al. (2016) in their study find that wind power increases hour-to-hour electricity price volatility as wind penetration increases, when looking at wind power forecasts. However, if not considering wind power forecasts, wind power decreases electricity price volatility. The main reason for this finding is that the mean electricity price reduces considerably and therefore the volatility is also reduced.

Ketterer (2014) argues that the price-decreasing impact of solar power is stable during peak hours (as also stated by Paraschiv Erni and Pietsch, 2014). As a result, solar power decreases price volatility in peak hours, as also found by Rintamäki et al. (2017). Because wind and solar power have opposite effects on daily price volatility, results on their combined impact are inconclusive.

Clò et al. (2015) studied the effect of increased wind and solar power on price volatility by looking at both daily averaged and hourly data for the Italian market. The paper finds that the increase in wind and solar generation amplifies wholesale electricity price volatility at around the same rate. Not surprisingly, the study affirms that looking at daily averaged data instead of hourly data smooths intra-day price volatility. This finding is later confirmed by Brancucci Martinez-Anido et al. (2016), comparing 5-minute to hour-to-hour data.

No conclusive evidence is found on the impact of renewables on price volatility. Gelabert et al. (2011) found a significant drop in the volatility of electricity prices in Spain. Over the same period, Woo et al. (2011) found that increases in wind generation tend to enlarge spot-price variance, as also found by Jacobsen and Zvingilaite (2010), Green and Vasilakos (2010), and Jónsson et al. (2010). Rai and Nunn (2020) also find that spot price volatility has risen. They show that higher volatility has been due to increased instances of spot prices being in the $100-

$500/MWh range, a range well below the historic range. Mwampashi (2021) even finds opposite signs for the effect of wind generation on electricity price volatility for different parts of Australia over the same period. A conclusion drawn from the finding is that states with high wind penetration are more susceptible to variation in electricity prices, as well as that the closure of coal-fired generators affects the markets. This may rely on the market structure of a region.

Rintamäki et al. (2017) conducted a study on renewable energy's influence on electricity prices in Denmark and Germany. The results are contradicting, as they find that in the short run, Danish daily price volatility is lower when there is more wind power production. By contrast, wind power increases the daily price volatility in Germany.

## 2.2 Electricity prices, COVID-19, and the Russian-Ukrainian conflict

The two recent disruptive events, despite being both global and startling, exhibit significant differences in the way they impact the global and local energy systems. The pandemic constitutes primarily an alteration in energy demand that has triggered a rapid, systemic, and global temporary change. On the other hand, the war has a direct impact on energy production, supply, and trade, while demand is influenced through actions and decisions by people to anticipate supply disruptions, impose sanctions on Russia, and decrease import dependency. During the pandemic, oil prices plummeted, in some instances to nearly zero or below, while during the war, they soared to over 100 USD/barrel.

### *2.2.1 COVID-19's influence on energy*

The demand for energy services was affected by the pandemic in many ways, mainly as a consequence of the related confinement measures. Working from home measures, travel restrictions, closure of public spaces, and access limitations to facilities and services restricted people's activities to the local level.

The pandemic led to a significant decrease in energy demand due to reduced mobility and economic activity. This resulted in a steep drop in global crude oil prices, raising concerns about the resilience of energy systems dependent on volatile international energy markets

(Kuzemko et al., 2020). Industrial disruptions and the shift towards online business further reduced electricity demand, while changes in lifestyle due to containment measures resulted in new energy consumption patterns (Zakeri et al., 2022).

The energy technology supply chain, including batteries and PV panels, was also adversely affected by the pandemic, particularly in intercontinental trade routes from China to other countries (Zakeri et al., 2022). The uncertainties associated with the supply chain, coupled with a lack of workforce mobility, project shutdowns resulting from lockdowns, and declining revenues from energy sales, collectively decreased the capacity of firms and governments to invest in energy projects (Andrijevic et al., 2020). Furthermore, unlike metals and agricultural goods, the energy sector will face the most severe return shocks (Farid, Naeem, Paltrinieri and Nepal, 2022), raising concerns about investments in green energy (Hoang et al., 2021).

After the lifting of lockdown measures in 2021, the industry resumed day-to-day activities in many regions of the world, leading to a surge in demand for energy carriers and consequent increases in energy prices. In particular, natural gas prices surged globally due to heightened demand in Asia and Europe, resulting in electricity and natural gas price hikes in 2021 (Zakeri et al., 2022). The situation became critical to low-income consumers who had already been negatively affected by the pandemic's economic repercussions.

*Green investments*

The politics of sustainable energy transitions are at a critical stage (Kuzemko et al., 2020). Due to confinement measures, disruptions in international trade, and reduced workforce availability, energy companies faced reduced investment capacity and delayed construction projects. As a result, there was a 10-15% decrease in new investments in clean energy projects in Europe compared to pre-pandemic levels (Eurelectric, 2020; Christopoulos, Kalantonis, Katsampoxakis and Vergos, 2021). This financial difficulty highlighted the vulnerability of centrally planned energy systems, and led to an increase in investment in onsite energy technologies post-COVID-19, such as solar-based applications in buildings and mini-grid systems in some developing countries (Ali, Aghaloo, Chiu and Ahmad, 2022).

*Volatility energy prices*

Devpura and Narayan (2020) examine oil price volatility and find a significant increase in volatility over the pandemic period. The paper shows that COVID-19 cases and deaths led to an increase in daily oil price volatility of between eight- and twenty-two percent, and show that as much as twenty-two percent of daily oil price volatility during COVID-19 was a result of the pandemic. Christopoulos et al. (2021) later confirms these results. Zhang and Hamori (2021) study the return and volatility spillover relation between COVID-19, the crude oil market, and the stock market. Their analysis concludes that return spillover mainly exists in the short term while volatility spillover is mainly found in the long term. The paper even finds that the pandemic's impact on oil volatility and stock market returns was more significant than the volatility caused by the 2008 financial crisis.

### *2.2.2 Russian-Ukrainian conflict*

Russia is the world's third-largest producer and exporter of oil, the second largest producer and largest exporter of natural gas, and the third-largest exporter of coal (BP, 2021). Consequently, the war has set off significant fluctuations and spikes in the prices of these commodities (among others). During the first half year of the conflict, there was a 60 percent escalation in coal prices and a surge of over 30 percent in European natural gas prices (Guénette, Kenworthy and Wheeler, 2022). Prices have exhibited large intraday variability. The rise in commodity prices comes on top of sharp increases since the pandemic. Moreover, production among OPEC+ nations has also been poorer than expected (Guénette et al., 2022). In April 2022, Russian exports made up over 35 percent of EU imports of natural gas, over 20 percent of oil, and around 40 percent of coal (Bachmann et al., 2022). Although Russia plays a crucial role as a global producer, the decisions made by OPEC will substantially influence the trajectory of prices too.

*Supply disruptions*

The war brought physical disruptions to the energy supply chain, which in turn activated the EU to focus more on green energy and energy independence. The bombing of infrastructure (including a nuclear power station) and the besiegement of major cities by Russian troops, along with the intentional sabotage of crucial assets by Ukrainian forces, have promptly caused substantial disruption to the energy supply chain. Ukraine operated 15 nuclear reactors at four distinct power plants. Between them, they provided around half of Ukraine's electricity. Last April, only seven reactors in Ukraine were still operational (International Atomic Energy Agency, 2022). Russia continued to export gas and oil to the EU in quantities of up to 1.4

million barrels per day (Brower & McCormick, 2022). Private sector entities have disengaged from involvement with Russia as well. Various oil and gas corporations have declared to withdraw from their stakes in oil and gas fields or companies. These include BP's 20 percent stake in Rosneft, ExxonMobil's participation in the Sakhalin-I project in eastern Russia, Shell's joint venture with Gazprom in the Sakhalin-II project, and all of Equinor's (Norway) Russian ventures (Benton et al., 2022).

## 2.3 Electricity spot market and market participants

### *2.3.1 Spot market*

In the Netherlands, the day-ahead and the intraday markets together make up the electricity spot market. Several operators run these markets, with EPEX and NordPool being among its largest (TenneT, n.d.).

The APX spot market comprises of two distinct market segments: the Day-Ahead Market (DAM) and the Intraday Market (IDM). The DAM, the larger of the two, operates as an auction-style market that determines the day-ahead prices for electricity for each 24 hour period of the following day. The IDM, on the other hand, enables participants to adjust their spot positions up to 5 minutes prior to the actual delivery of electricity. As of March 2013, the Dutch IDM is coupled with the Belgian and Nord Pool Intraday markets (Tanrisever, Derinkuyu and Jongen, 2015).

### *2.3.2 The day-ahead market*

Most of the electricity not traded on the forward markets trades on the day-ahead market (Epexspot, 2021). The day-ahead market is a spot market in which participants can trade spot electricity for physical delivery the next day. Participants frequently use the day-ahead market to alter positions from the forward market due to forecasting errors. In this way the market can provide flexibility a day before the actual electricity is delivered and consumed (Van Hout, Koutstaal, Ozdemir and Seebregts, 2014). The DAM uses a two-sided, double-blind auctioning structure. That is, both buyers (retail companies or large consumers) and sellers (power generators) may place anonymous orders with different prices and quantities hourly. These orders produce supply and demand curves for each hour of the following day (Swider, 2007). All parties may submit bids and offers for power delivery once the DAM opens at midnight the day before. Then at 11:00, the transmission system operators publish the available transmission capacity (ATC), which indicates how much capacity will be available during each hour of the delivery day. At 12:00, the auction closes and a matching algorithm, COSMOS, takes all bids from the participants and uses the constraints imposed by the transmission lines to come up with the best clearing prices that maximize social welfare (Epexspot, 2011). The auction result is published at 12:55 on the APX website and acts as a reference for other electricity markets (Tanrisever et al., 2015). APX acts as the central counterparty for all trades on its platform, where all contracts are executed anonymously. The contracts traded on the exchange are fully collateralized, as all members are mandated to provide collateral in the form of cash or a letter of credit that exceeds their outstanding exposures at all times.

### *2.3.3 The intraday market*

After the DAM market closes it announces the hourly prices to all market participants. However, during the time between the determination of the day-ahead positions and the physical delivery of electricity, market participants may decide to update their physical positions. This is done through the intraday market. In recent years the trading volumes on the intraday market have been growing, although this amount is still small compared to traded volumes in the day-ahead market (Tijdink & Muller, 2020). Especially the introduction of renewable energy has sparked more interest in the intraday market. Since renewable power production is difficult to forecast ahead of time, electricity suppliers can adjust their positions close to delivery in the intraday market (Van der Welle, 2016). The participants in this market can adjust their spot positions up to five minutes before the physical delivery of electricity. Buying electricity in the intraday market is generally more expensive than the day-ahead market (Pape, Hagemann and Weber, 2016). The reason for this is that the intraday market allows for more flexibility in buying and selling electricity at short notice, which can come at a premium. In the day-ahead market, prices are set in advance through an auction process, while in the intraday market, prices are determined based on supply and demand in real time.

However, this is a relatively new market with limited data availability. This combined with the fact that the trading volumes are still relatively small and come at higher prices, drives us to exclude them from this thesis.

## 2.4 TenneT

### *2.4.1 Transmission System Operators (TSO) & Distribution System Operators (DSO)*

TSOs operate the high-voltage electricity grid. This entails fundamental system functions, including continuously controlling and monitoring the grid's electrical supply and demand balance. To ensure that that is possible, TSOs are also in charge of organizing, maintaining, and growing the high voltage grid (above 110kV) serving present and future market needs. TSOs work together to create a single European electricity market and provide the most effective resource allocation to enable a smoothly operating electricity market.

The regional distribution grid, which DSOs run, distributes electricity from the high voltage system to final users. Just like the TSO, they are responsible for the planning, construction, maintenance and operation of the distribution grids (TenneT, n.d.). Among other smaller tasks, they add new participants to the grid and are responsible for the registration, management and exchange of data used by market parties (TenneT, n.d.).

TSOs are in charge of maintaining the system's overall stability, while DSOs and TSOs are jointly responsible for avoiding grid congestion.

### *2.4.2 TenneT*

TenneT, a state-controlled monopoly, serves as the backbone of the Dutch electricity market and oversees the management of the electrical grids larger than, and including, 110kV. Through its network, all regional grids in the Netherlands are interconnected and connected to the broader European network. As a lone buyer, TenneT is assigned the responsibility of procuring reserve capacity from Dutch energy producers in exchange for the transmission of their electricity. TenneT defines this capacity as "the capacity they can produce or consume over or under the amount reported in their E-programme" (TenneT, n.d.).

Before the physical delivery of electricity, TenneT requires market participants to furnish two sets of information, the T-prognosis and the E-program. The T-prognosis, which comprises a forecast of the flow of electricity, is utilized by TenneT to guarantee the electrical grid's stability. The E-program represents the net position of each market participant for every unit of time within the program. To guarantee the balance of demand and supply on the grid, Tennet must approve all E-programs. To avoid extremely high or low prices, TenneT expects its suppliers and extractors to participate in balancing the grid (TenneT, 2018).

## 2.5 Energy policy and subsidy schemes in the Netherlands

### *2.5.1 Pre-2003*

In the early 1990s, the government negotiated voluntary agreements with the energy distribution sector, which committed itself to voluntary sales targets for renewables amounting to 3.2% of electricity sales and 0.7% of gas sales by the year 2000 (Van Rooijen & Van Wees, 2006). In 1996, the government introduced a regulatory energy tax, also known as the ''ecotax'' for small- and medium-scale energy users. This new tax system stimulated green electricity consumption. In 2002, total support for green electricity amounted to eight eurocents per kWh (comprised of six eurocents for consumer support and two eurocents for production support) (Van Rooijen & Van Wees, 2006).
The following important phase of Dutch green electricity policy was a liberalization of the green consumer market in 2001.

### *2.5.2 MEP*

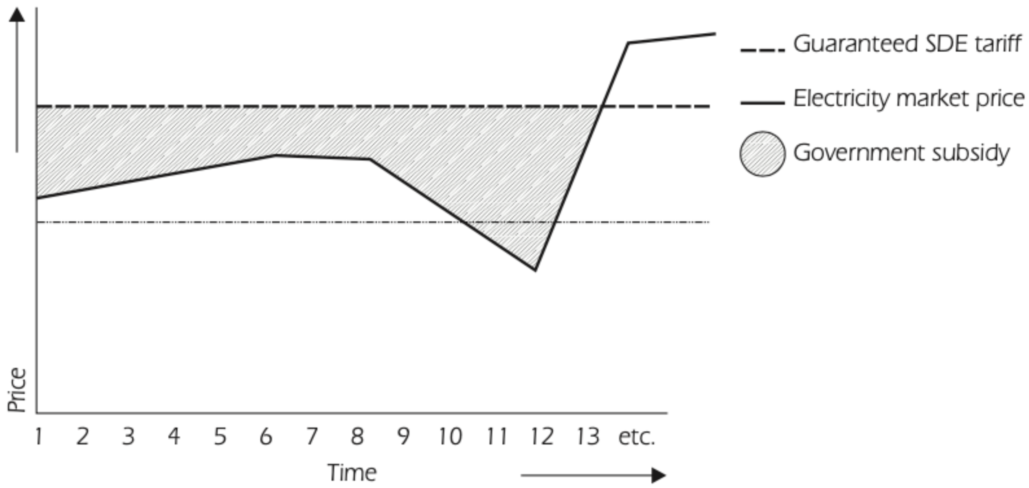
A (new) policy, called the "environmental quality of electricity production'' (MEP), was implemented in July 2003. The MEP had two main objectives: to reduce investment risk and to improve the cost-effectiveness of renewable electricity. MEP subsidized costs for renewable electricity generators through a premium on top of the electricity price for the extra "green" costs of renewable generation. Support is provided using a feed-in tariff, combined with a partial exemption from the ecotax, where an annual levy on the electricity connections of every household finances the tariff (Van Rooijen & Van Wees, 2006). The ecotax exemption phases out over two years. In effect, MEP functioned as a differentiated premium scheme; producers were provided a fixed subsidy per kilowatt-hour, depending on technology, earned on top of the revenue for the sale of electricity in the wholesale market. The subsidies in 2006 ranged from a low of 1.3 eurocents per kWh for landfill gas and digestion to 9.7 eurocents per kWh for offshore wind, solar, PV, small biomass, hydro, and wave power (International Energy Agency, 2009).

### 2.5.3 SDE

In 2008, the MEP became the "Stimulation of Sustainable Energy production'' (SDE) scheme (Staatscourant, 2008). The SDE scheme, implemented for a period of two years, utilized a compensation mechanism that calculated subsidy amounts based on the assumption that the production of electricity from fossil fuels was more cost-effective than the production from renewable energy sources. The revised scheme, known as the modified feed-in tariff scheme, represents a departure from the previous premium scheme. A fixed subsidy is guaranteed as a feed-in tariff, with an option for a higher price per kWh if the electricity price goes above the subsidy ceiling (International Energy Agency, 2009). The subsidy for renewable suppliers was dependent on the price of electricity and/or gas as a compensation, and was granted for a period of twelve- to fifteen years (Staatscourant, 2008).

In practice, renewable energy generators received a specific price per kWh. Should the price of electricity fall below the established ceiling, the government compensates the generators with the differential. Conversely, if the market price is equal to or surpasses the established ceiling, the generator will not receive any subsidies from the government. In summary, the subsidy has a maximum threshold, and the price paid to generators has a minimum threshold; generators will only receive payment above the subsidy ceiling if the electricity price exceeds the established threshold. Figure 2 shows a schematic of the SDE's modified feed-in tariff scheme.

Figure 2: Variability of SDE Subsidy According to Electricity Market Price




Source: International Energy Agency (2009)

### 2.5.4 SDE+

In 2011 the SDE+ program was introduced. The primary distinction between the SDE and SDE+ programs is that the former allocated a specific budget for each renewable energy technology, whereas the latter allocated a consolidated budget for all renewable energy technologies collectively (RVO, 2019). The implementation of feed-in tariffs and the provision of supplementary funding have served as catalysts for the emergence of renewable energy entrepreneurship in the Netherlands. This, in turn, had a significant impact on the composition of the country's energy mix.

## 3. Research Question & Hypotheses

As discussed in the introduction, we distinguish the following periods:
2018-2019 Base case (benchmark of our study)
2020-2021 COVID-19 pandemic (reduced demand)
2022 Russian-Ukrainian conflict (supply chain distortions)

From the literature we expect to find lower prices and higher volatility due to a higher amount of renewable electricity in the Dutch electricity grid. This paper aims to relate the effects of events in these periods to Dutch electricity prices and their volatility in the day-ahead market. This paper studies the following research question:

*How does the influence of a growing share of renewable electricity generation on Dutch day-ahead electricity prices and their volatility evolve over periods of low demand and supply chain disruptions?*

In the base case, we expect renewable electricity generation to grow in the grid, leading to lower average prices and higher volatility. We propose the following hypotheses for the base case:

$H1_0$: *In the base case, Dutch day-ahead electricity prices do no decrease due to renewable electricity generation.*
$H1_1$: *In the base case, Dutch day-ahead electricity prices decrease with the addition of renewable electricity generation.*

$H2_0$: *In the base case, the contribution of renewable electricity does not influence electricity price volatility.*
$H2_1$: *In the base case, the contribution of renewable electricity positively affects electricity price volatility.*

During the COVID-19 pandemic, electricity demand and renewable investment decreased. Previous literature finds that the volatility of energy prices has increased. With output going down during the pandemic, we expect the share of renewables in the grid to rise. This together makes for the following hypotheses:

$H3_0$: *Dutch day-ahead electricity prices were not lower during the pandemic compared to the base case.*
$H3_1$: *Dutch day-ahead electricity prices were lower during the pandemic compared to the base case.*

Prices in this period are assumed to go down, which would ceteris-paribus decrease volatility too. At the same time, the pandemic and the uncertainty during those times raise volatility. Renewable output is assumed to increase compared to the base case, which would lead to increased volatility. Hence, we hypothesize that the relationship between the pandemic and electricity price volatility is positive.

$H4_0$: *There is no difference in the impact of renewable electricity generation on Dutch day-ahead electricity prices during the pandemic compared to the base case.*
$H4_1$: *Renewable electricity generation has a more substantial impact on Dutch day-ahead electricity prices during the pandemic compare to the base case*

$H5_0$: *During the pandemic, the contribution of renewables to the Dutch electricity grid does not increase electricity price volatility compared to the base case.*
$H5_1$: *During the pandemic, the contribution of renewables to the Dutch electricity grid increases electricity price volatility compared to the base case.*

Lastly, during the Russian-Ukrainian conflict and all its implications for the electricity supply chain, the following hypotheses are proposed:

$H6_0$: *Dutch day-ahead electricity prices were not higher during the war compared to the base case.*
$H6_1$: *Dutch day-ahead electricity prices were higher during the war compared to the base case.*

$H7_0$: *There is no difference in the impact of renewable electricity generation on Dutch day-ahead electricity prices during the war compared to the base case.*
$H7_1$: *Renewable electricity generation has a more substantial impact on Dutch day-ahead electricity prices during the war compared to the base case.*

$H8_0$: *During the war, the contribution of renewables to the Dutch electricity grid does not increase electricity price volatility compared to the base case.*
$H8_1$: *During the war, the contribution of renewables to the Dutch electricity grid increases electricity price volatility compared to the base case.*

# 4. Data

## 4.1 Datasets

This data section provides an overview of the data used for this study, containing descriptive statistics and data sources. All data used are measurements of the Dutch day-ahead electricity market. Please note that “Dutch day-ahead electricity prices” can be referred to throughout this study as “electricity prices”.

The dataset employed in this study includes two time series ranging from 01/01/2018 up to, and including, 31/12/2022, totaling 1,826 observations.
The first time series is the Dutch APX day-ahead electricity spot price. APX power NL is an independent electronic exchange for the electricity market. ENTSO-E, a platform for the central collection and publication of electricity generation, transportation and consumption data for the European market, releases the data. The data is aggregated and retrieved through DataStream and a third-party website called Energy-Charts. The series contains the daily values for electricity prices in euros per megawatt hour for all days, and hourly values for weekdays.

The second time series is daily renewable electricity generation for public power supply in megawatts. The data is sourced from ENTSO-E and EEX and collected and published by Energy-Charts. We aggregated the time series into the total generation of offshore wind electricity, onshore wind electricity, and solar PV. The resulting dataset contains 1,826 observations. Appendix 1 presents a table containing the variables and time periods used in this study, including a brief description.
One of the advantages of working with these datasets is the quality of data. Since the values are all official reports from national markets, no measurement errors are found in the data unless reporting errors exist.

## 4.2 Summary Statistics

Several distinguishing features characterize the behavior of prices, beginning with its regular intraday variation. This is seen quite clearly in Figures 3 and 4. Figure 3 presents the daily averages of electricity prices measured in euros per megawatt hour. The prices exhibit an inverted s-shaped pattern. Prices seem to follow a downward trend in the period of 2019 up to around June 2020, whereafter they strongly rise. As for the negative pricing characteristics of electricity prices: this is not recurrently seen in the plot. Over the past five years, prices have been relatively high, and days where the average electricity price is negative are not observed frequently in the data.

Figure 3: Average Daily Electricity Price 2018-2022 (EUR/MWh)

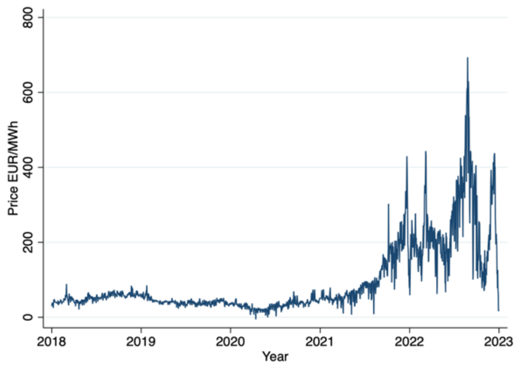



Figure 4 shows the average weekly price in euros per megawatt hour. The same pattern is found, but looking at weekly averages, prices exhibit less volatility. The inferences made still hold but are more nuanced.

Figure 4: Average Weekly Electricity Price 2018-2022 (EUR/MWh)

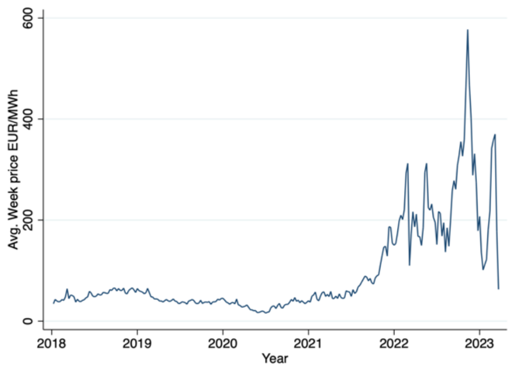
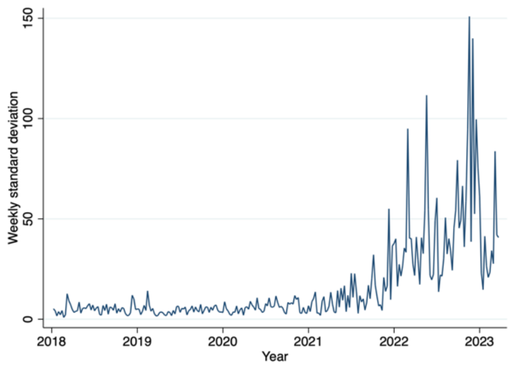



Figure 5 presents our sample's weekly standard deviation. Standard deviation follows roughly a similar pattern as prices do. However, over the years 2018-2021, where prices were less extreme in value, the standard deviation shows a more consistent pattern. In 2022, when prices had risen sharply, standard deviation exhibited similar behavior.

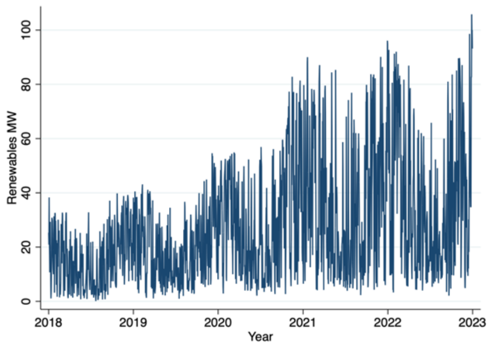
Where in the previous figures we saw an inverted s-shaped pattern, here we can see that standard deviation remained relatively constant over the years 2018 to 2021, whereafter in 2022 it rises sharply. Due to the fact that over the first years prices had gone down, but volatility had gone up, we believe volatility to increase over the entire duration of our sample.

Figure 5: Weekly Standard Deviation 2018-2022




Let us look at our second time series: renewable electricity generation over time. The exogenous variable used in the models is the number of megawatts of renewable energy[1] produced in the Netherlands. Figures 6 and 7 show the total renewable energy generated in the Netherlands over our sample period. Not surprisingly, the series displays a positive trend over our time period. Next to the rising output, we can see a seasonal pattern in the data, where more renewable electricity is generated in the Netherlands during the winter months.

Figure 6: Daily Renewable Electricity Generation 2018-2022




[1] The aggregate of wind and solar power

Figure 7: Weekly Renewable Electricity Generation 2018-2022

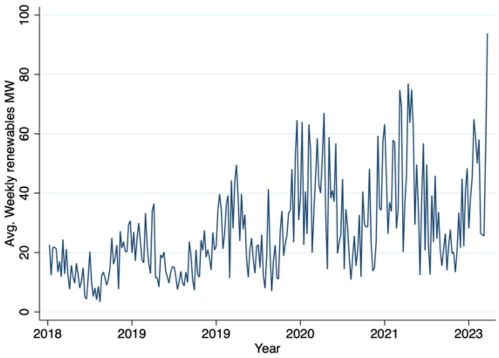



Table 1 presents the summary statistics for our sample. Negative prices were uncommon over the past five years. Further, the maximum price of nearly €700 per MWh is unprecedented. We can see that starting from the base case, the mean electricity price follows a rising trend over time. The maximum price over the periods follows this pattern. Moreover, the volatility of electricity prices significantly rises over time. Table 2 shows the weekly averages for the three time periods and reaffirms our findings.

Table 1: Summary Statistics (EUR/MWh)

| **Variable** | **Observations** | **Mean** | **St. Dev.** | **Minimum** | **Maximum** |
|---|---|---|---|---|---|
| Price full sample | 1,826 | 94.15 | 98.11 | -5.45 | 693.83 |
| Price base case | 730 | 46.86 | 10.88 | 20.90 | 88.98 |
| Price pandemic | 731 | 67.58 | 60.41 | -5.45 | 429.84 |
| Price war | 365 | 241.93 | 113.57 | 16.38 | 693.83 |
| Renewables[Ψ] | 1,826 | 27.27 | 21.21 | 0.1 | 105.8 |

Table 2: Summary Statistics Week Averages (EUR/MWh)

| **Variable** | **Observations** | **Mean** | **St. Dev.** | **Minimum** | **Maximum** |
|---|---|---|---|---|---|
| Price full sample | 261 | 94.13 | 94.93 | 15.85 | 577.27 |
| Price base case | 104 | 46.89 | 9.73 | 33.29 | 65.89 |
| Price pandemic | 104 | 67.11 | 58.46 | 15.85 | 312.39 |
| Price war | 53 | 239.86 | 102.64 | 62.85 | 577.27 |
| Renewables[Ψ] | 261 | 27.30 | 16.32 | 3.39 | 93.88 |

[Ψ] In megawatt

### 4.3 Structural break test

Noticeably, this study hypothesized prices during the pandemic to decrease, but this is not found in our summary statistics. The pandemic came to the Netherlands around March 2020, and its rebound effects already showed in 2021. The steep increase in demand right when COVID-19 allowed businesses to start operating more freely dampens the effect of fallen demand during the better part of the pandemic period. To test this more formally, we conduct a Zivot-Andrews structural break test.

A structural break occurs when there is a significant change in the behavior of the time series, such as sudden increases or decreases in mean values or trends. The Zivot-Andrews endogenous structural break test is a test which utilizes the data series and uses a different dummy variable for each possible break date. It tests the null hypothesis that the series has a unit root with a structural break. The break date is selected where the t-statistic from the test of a unit root is at its lowest value. Consequently a break date is chosen where the evidence is least favorable for the null hypothesis (John, Nelson and Reetu, 2007). The test identified a break in the intercept of the regression, with a minimum t-statistic of -5.81. We conclude that a structural break occurred in the price series at week 36 of 2021 (30/08/2021).

Consequently, we redefine the periods of our study. Speculation preceded the Russian invasion of Ukraine which took place in February 2022, but we do not want to overestimate this speculation. Consequently, we define the remainder of 2021 after the structural break as the COVID-19 recovery period, and define the period of war as the year 2022. We split the pandemic period, resulting in the following four periods:
01/01/2018 – 31/12/2019 Base case
01/01/2020 – 05/09/2021 Pandemic 1, representing the period of fallen demand
06/09/2021 – 31/12/2021 Pandemic 2, representing the period of rising demand
01/01/2022 – 31/12/2022 War

Table 3 shows the corresponding summary statistics. We should take into consideration that the sample size for the second pandemic period is relatively small. We can see that the price pattern now follows our hypothesized course. Interesting is how during the period of fallen demand, the drop in mean prices is relatively small. We have seen that with the outbreak of COVID-19, prices have fallen. These drops over time likely correlate with government confinement measures taken against the spread of the virus. We assume that the higher the impact of the measure, the lower electricity demand will be. We expect that the aggregate effect over our time period smooths out with the aggregation of effects when measures are (temporarily) lifted. Studying the effects of renewables throughout the pandemic in more detail could be interesting, but is left for further research.

Table 3: Summary Statistics Redefined Periods – Price Daily Averages (EUR/MWh)

| **Variable** | **Observations** | **Mean** | **St. Dev.** | **Minimum** | **Maximum** |
|---|---|---|---|---|---|
| Full sample | 1,826 | 94.15 | 98.11 | -5.45 | 693.83 |
| Base case | 730 | 46.86 | 10.88 | 20.90 | 88.98 |
| Pandemic 1 | 614 | 45.33 | 22.49 | -5.45 | 124.07 |
| Pandemic 2 | 117 | 184.36 | 62.58 | 74.11 | 429.84 |
| War | 365 | 241.93 | 113.57 | 16.38 | 693.83 |

Table 4: Summary Statistics Redefined Periods – Price Week Averages (EUR/MWh)

| **Variable** | **Observations** | **Mean** | **St. Dev.** | **Median** | **Minimum** | **Maximum** |
|---|---|---|---|---|---|---|
| Full sample | 261 | 94.13 | 94.93 | 51.59 | 15.85 | 577.27 |
| Base case | 104 | 46.89 | 9.73 | 43.45 | 33.29 | 65.89 |
| Pandemic 1 | 88 | 45.30 | 20.73 | 41.07 | 15.85 | 111.44 |
| Pandemic 2 | 16 | 187.08 | 53.19 | 179.97 | 128.78 | 312.39 |
| War | 53 | 239.86 | 102.65 | 213.39 | 62.85 | 577.27 |

*Significance sample averages*

Ideally, we would want to formally test whether our sample groups differ significantly from each other in their average price values. Unfortunately, our groups do not satisfy the conditions for either parametric- or nonparametric tests.

Commonly used tests are the t-test or alternatively the Wilcoxon rank-sum test. An overview of all the suggested tests and the shortcomings of our series for their assumptions is presented in Appendix 2. Transforming our data to exhibit a normal distribution would enable us to test for differences among the sample means formally. Common transformations such as taking logarithms or squaring values of our data do not yield a distribution that satisfies the necessary assumptions for testing. As an additional ad-hoc check, we add the median to the summary statistics in Table 4. We can see that both the mean and the median follow the trajectory as suggested by our hypotheses. The median of 41.07 in the pandemic period of fallen demand reaffirms the finding of the mean value, stating that over the period prices have not fallen by much compared to the base case.

# 5. Methodology

This study uses the family of Autoregressive Moving Average (ARMA) models. Our approach consists of two stages: identification of the specific ARMA model(s) and estimation and verification. Let us start by taking a closer look at the properties of our dataset.

## 5.1 Distributional properties and model identification

### *5.1.1 Price series*

For our study, Autoregressive (AR) Moving Average (MA) models will be used to study our hypotheses. Two main underlying assumptions need to be satisfied to ensure the validity of their use. First, for using AR models, the price series needs to exhibit stationarity. A series is said to be stationary if it:

1. Exhibits mean reversion
2. Has a finite and time-invariant variance
3. Has a diminishing autocorrelation function as the lag length increases

Second, for the use of the MA component of the model, it is essential that the invertibility condition is satisfied. Invertibility ensures that the model's parameters can derive a formula that expresses the current observation in terms of past error terms rather than only past observations. This implicitly assumes that an autoregressive model can approximate the series.

Given the non-storable nature of electricity, real-time matching of supply and demand is necessary to avoid temporary imbalances, which may result in extreme prices. However, we expect these prices to revert to a more stable state once supply and demand are equal. Hence, when constructing price models, one should consider mean reversion as a common phenomenon in electricity markets (Huisman & Mahieu, 2003; Ketterer, 2014). Another critical characteristic of electricity prices is seasonality. The demand for electricity exhibits variation across different times of the day, week, and year. Therefore, seasonal fluctuations should be accounted for in electricity price models, as demonstrated in studies by Knittel and Roberts (2005), Lucia and Schwartz (2002), and Ketterer (2014). Moreover, the series must exhibit a constant variance. The fluctuations in the price over time should not be too extreme or unpredictable, but rather fluctuate within a certain band. This assumption is commonly satisfied in electricity prices, where we do not expect extreme, sudden changes in prices from one day (or week) to the next. Stationarity for our dataset will be formally tested further in this section.

*Distributional properties*

Figure 8 presents the empirical histogram for our price series overlaid with a normal density curve. Figure 9 presents a QQ-plot of the data. In the QQ-plot, normally distributed data will appear linear. Both figures illustrate the deviation from normality for our dataset. Our price series exhibits a (positive) right tail distribution, indicating relatively high skewness in our data.

Figure 8: Empirical Histogram Price Series

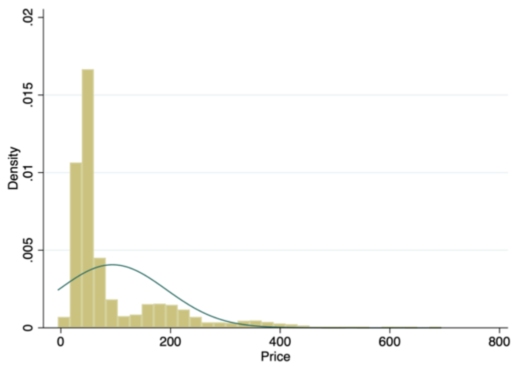
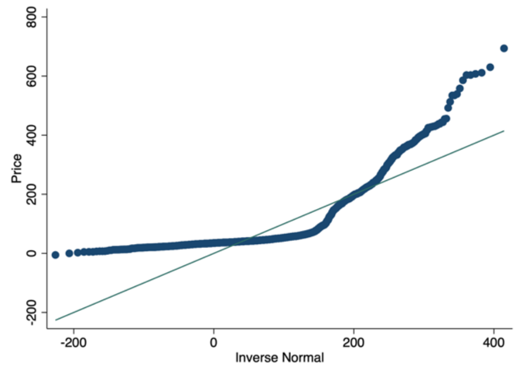



Figure 9: QQ-Plot Price Series




In the autocorrelation function (ACF) in Figure 10 we can see a diminishing trend, but likely not at a geometrically fast rate. The autocorrelation values remain statically significant well beyond 40 lags. If the values were independent of their past values, we would expect the autocorrelation function to decay rapidly and remain within the 95% confidence interval. The confidence interval defines the range of values that we expect to see 95% of the time if the time series is white noise. When the observed values fall outside this interval, we can conclude that they are not statistically significantly equal to zero. White noise entails that we are dealing with a sequence of random values. If we were dealing with white noise, we would not expect to see any significant autocorrelation beyond some small number of lags. Since we see significant values well beyond 40 lags, we conclude that we are not dealing with white noise here.

The partial autocorrelation function (PACF) shows the partial correlation of a time series with its own lagged values. The PACF differs from the ACF in that it only measures the correlation between the time series and its past values at a certain lag after removing the effects of intervening lags. In Figure 11 we can see that the first lag has a considerably high value, which suggests a strong correlation between the first and second observations after accounting for the influence of intervening lags. This reaffirms our use of an AR model. We can see a steep drop to a value within the confidence interval in lag 2. Values within the confidence interval suggest no significant correlation between the observations. Here for, the figure suggests that the time series does not significantly exhibit memory beyond one lag. Additionally, a seasonal pattern is deducted from the figure. Most noticeable are the negative values at lags 8, 15, 22, …, which refer to the lower demand over the weekend compared to weekdays. This is a widely found phenomenon in the literature (among many others found by Knittel & Roberts, 2005; Rintamäki et al., 2017; Mauritzen, 2010). In conclusion, the PACF, exhibiting a strong correlation at the first lag and a weekly seasonality pattern, suggests that an AR(1) model with weekly seasonality effects and a weekly moving average term can describe the data well.

Figure 10: Autocorrelation Function Price Series

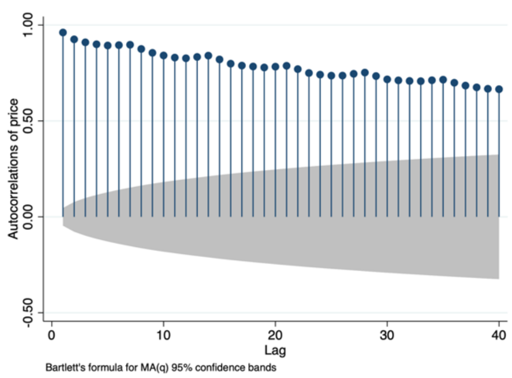
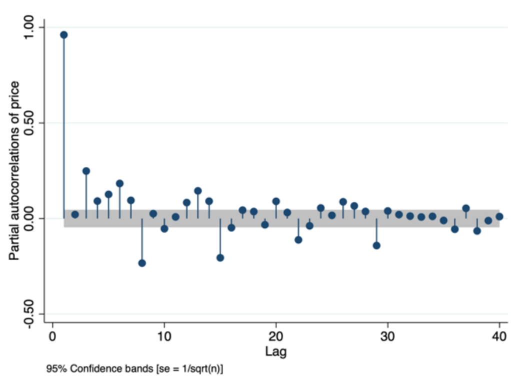



Figure 11: Partial Autocorrelation Function Price Series




To further test how autocorrelation decays over time, we consider the following simplified model for the price-generating process:

$$P_t = \alpha + \beta P_{t-1} + \eta_t \tag{1}$$

$$\eta_t = \gamma \eta_{t-1} + \varepsilon_t \tag{2}$$

Where $P_t$ is the price at time $t$, $\alpha, \beta$, and $\gamma$ are unknown coefficients, and $\varepsilon_t$ is a white noise process with variance $\sigma_\varepsilon^2$. If serially correlated errors are present, Phillips and Perron (1988) show that the price process parameters can be estimated by ordinary least squares regression. First, a Durbin-Watson test[2] is performed, which yields a d-statistic of 2.04. Hence, we can safely conclude on our data not exhibiting first-order serial correlation. To further inspect stationarity, a unit root test is performed. The presence of a unit root entails that the data has a systematic tendency to follow some path over time (for instance, rising over time). This tells us that the data in the series is not stationary. The unit root test formally checks whether a time series is stationary. We have stated earlier that when dealing with autocorrelation, values in a time series and their past values correlate. Hence, the assumption of independence errors, required for the unit root test, does not hold in the presence of autocorrelation. To test this, we can use the Newey-West corrected t-statistic. This value takes autocorrelation into account and adjusts the test accordingly. The Newey-West corrected t-statistic under the null hypothesis of a unit root is 68.99, and we reject the null hypothesis that the time series has a unit root at the 1% significance level. We can conclude that the data is stationary and has "clean" white noise errors.

### *5.1.2 Renewable electricity generation*

Figures 12 and 13 plot the ACF and PACF of the renewables data. We see similar patterns as in the price series. The ACF displays dissipating autocorrelations, this time with a steeper drop after the first lag. The PACF shows a drop after the first lag, whereafter, the values (nearly) fall within the confidence interval. As seen in the price series PACF, a weekly seasonal pattern is again found. Again, the figures suggest that an AR(1) representation may adequately describe the autocorrelation structure of the data.

[2] Widely used test in econometrics to check for first-order autocorrelation; see Durbin and Watson (1950)

Figure 12: Autocorrelation Function Renewables

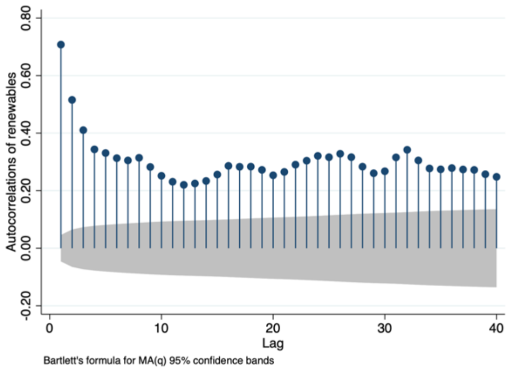
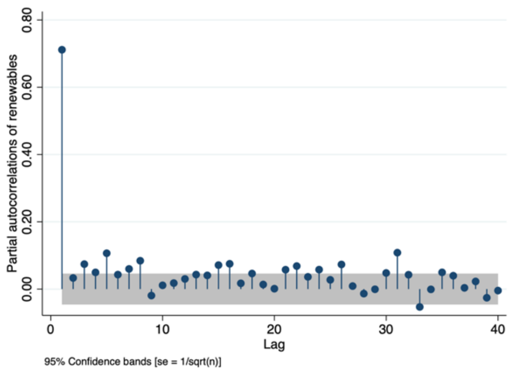



Figure 13: Partial Autocorrelation Function Renewables




When adding renewable electricity generation, the resulting dataset must satisfy two assumptions. First, both the price series and the exogenous series must be stationary. We have proved the price series to be stationary. We take similar steps to arrive at stationarity for the renewables data. First, we yield a Durbin-Watson test statistic of 2.04 for the renewable generation data. We then run an Augmented Dicky-Fuller (ADF) test with one lag. The test statistic is -15.55, and we can reject the null hypothesis of at least one unit root at the 1% significance level. We chose an ADF test here since we expect serial correlation to be less likely in the series. This motivates our choice of the ADF test because the test takes into account the potential for serial correlation in the residuals. To verify stationarity, we check the results with a Newey-West test which, with a t-statistic of 42.02, rejects the null at the 1% level. Based on the observed patterns of the ACF and PACF and applying the same logic used for the time series analysis, we can conclude that an ARMAX model is appropriate. Again, we should take weekly seasonality into account. We observe a similar pattern as seen in the price series, which we expect given the influence of past weather on current weather conditions. For instance, the weather being windy today makes it likely for the weather to be windy tomorrow as well.

For the use of ARMA models, two conditions must be satisfied. We have shown that the stationarity and invertibility assumptions are satisfied for our data set. For the extension to an ARMAX model that includes renewable generation as a variable, we must show that renewable electricity generation is an exogenous variable.

An advantage of renewable electricity generation as a variable is that it is a passive form of generation (Mauritzen, 2010). The production of solar PV and wind energy is contingent upon the availability of said factors. Since the marginal costs of production are nearly zero, producers do not have much incentive to limit production due to price signals. Hence, we conclude that the renewable electricity generation is highly likely to be exogenous to prices.

The literature mentions two possible exceptions to the assumption of exogeneity. Firstly, there is a possibility that the system operator could order renewable energy offline due to balancing considerations, which may influence the price. This is likely a minor factor as Mauritzen (2010) shows. Second is the possibility that market power is exercised. A large energy producer that utilizes a diverse array of generation technologies, including significant solar PV and wind power components, may be incentivized to curtail renewable electricity output to benefit from higher prices. In the Dutch energy market, Tennet has the role of market maker and the Dutch government regulates Tennet in a public-private partnership where the state owns 100% of the shares. Tennet closely monitors its TSOs and has the power to penalize players that do not act in the market's best interest. Additionally, it is less likely to exercise market power over extended periods of time. Here for, the risk of market manipulation occurring reduces when looking at weekly aggregated data instead of daily data. Henceforth, this paper assumes that the risk of exercising market power is neglectable and we conclude that renewable electricity generation is exogenous.

### *5.1.3 Data aggregation*

The presence of seasonality in our data has become evident. Though a consistent yearly price pattern is not apparent, we observe a weekly pattern. Some studies remove weekend observations to mitigate the effects of this weekly seasonality. Other studies add dummy variables for weekdays to investigate the weekday versus weekend effects. In our study, we aim to observe what happens with prices and price volatility over a period of five years, including the effects of renewable electricity generation. We argue that the movements in these parameters shown over the years do not change when using weekly aggregated data instead of daily data.

One could argue that our statistical inference is less powerful because our observation count is reduced by a factor seven. However, many previous studies find similar trends when extending daily data regressions with weekly aggregated data regressions (see for instance Maurtizen, 2010).

Using weekly data offers our study benefits that motivate our choice to use it. First, by using weekly averaged data, the weekly seasonal effect found is accounted for in the dataset without removing observations. Moreover, outliers are smoothed out by aggregating the data, which decreases the need for data cleaning for our sample. Second, one might argue that our study could benefit from extending our study by adding AR(2), or MA(2) factors to our models, thereby removing noise in the data. Looking at daily data, one could potentially substantiate this argument. It is, however, unlikely that it adds explanatory power when adding factors that state that results from a seven-day period relate to periods of fourteen days earlier, let alone higher-order lags. This is firstly the case for the price series, but arguably even more so for the renewable generation series. We have seen the steep drop in its PACF going from one lag to two lags, and we know that weather conditions on day $t$ strongly correlate with weather conditions on day $t + 1$. When it is sunny or windy today, chances are that the forecast for tomorrow is similar. By aggregating the data at a weekly level, we can more accurately capture the longer-term trends and patterns in the data, which the variability of daily data can obscure. Many factors can cause daily fluctuations in renewable generation. Averaging out these fluctuations over a week reduces the noise in the data, making the underlying trend more apparent. This is especially useful for long-term trend analysis, where the main focus is on the overall pattern over time rather than short-term fluctuations (Haug, 2002). Lastly, for our ARMAX model, the renewables variable must be exogenous, and we have shown that using weekly data lowers the chances of validating this assumption.

We transform the data by arithmetically averaging seven daily observations, resulting in 261 observations. Our weeks range from Monday to Sunday, and only 2022 has 53 weeks[3]. This is because out of this 53rd week, six days fall within the year 2022.

## 5.2 Models

*Simultaneity*

In our models, regressions involve both price and quantity variables. Consequently, simultaneity becomes a potential problem when making our inferences. Moreover, using weather variables that affect consumption (such as temperature) as instruments for the quantity variables is not appropriate as those are likely to be correlated with renewable energy

[3] With the last week consisting of six days

generation. Though let us think about how simultaneity affects our variables. Various factors influence the quantity of electricity demanded, including the price of electricity, weather conditions, and the time of day. When electricity prices increase, consumers may reduce their electricity demand, which particularly occurs during periods of peak demand when prices are highest. Conversely, when electricity prices decrease, demand may increase. Therefore, the quantity of electricity demanded is a function of price and other exogenous factors, such as weather and time of day. Electricity demand is, however, known to be highly inelastic in the short run, especially for end consumers. Moreover, independence of weather conditions from demand-side factors is not a necessary condition to get valid inferences, as long as we treat renewables as an exogenous variable. For these reasons, we assume simultaneity will not reduce the significance of our results or their interpretations.

*Models*

This section presents the models used in our study of electricity prices. We estimate the models for five samples: the full sample and the four subsamples, as defined in this paper's data section.

Autoregressive Moving Average Models are a common way to describe time series. The ARMA($p, q$) model consists of autoregressive terms, $p$, and moving average terms, $q$. The orders of the model describe how many past values explain the movement in the explanatory variable.

The first term refers to the autoregressive model of order $p$. The model AR($p$) is given by:

$$X_t = \varepsilon_t + \sum_{i-1}^{p} \varphi_i X_{t-i} \tag{3}$$

Where $\varphi_1, \ldots \varphi_p$ are parameters and the random variable $\varepsilon_t$ is the white noise[4].

The second term refers to the moving average model of order $q$. The model MA($q$) is given by:

[4] Independent and identically distributed normal random variables

$$X_t = \mu + \varepsilon_t + \sum_{i-1}^{q} \theta_i \varepsilon_{t-i}$$

*(4)*

Where the $\theta_1$, … $\theta_q$ are parameters, $\mu$ is the expectation of $X_t$, and the $\varepsilon_t$, $\varepsilon_{t-1}$, … are again white noise error terms.

The ARMA($p, q$) model in its general form is then given by:

$$X_t = \varepsilon_t + \sum_{i-1}^{p} \varphi_i X_{t-i} + \sum_{i-1}^{q} \theta_i \varepsilon_{t-i}$$

*(5)*

*Choosing values for p and q*

In section 4.1.1, we have shown from the ACF and PACF that choosing an autoregressive term of value $p = 1$ fits our data well, especially when looking at weekly aggregated data. Secondly, we must choose the value of our moving average term. Based on our analysis in section 4.1.2, we have determined that an MA(1) model is appropriate since weekly data tends to exhibit short-term fluctuations or noise that can be captured well by a first-order moving average term. Generally, higher-order MA models may be appropriate if the data has more persistent noise (in our case over multiple weeks). While higher-order MA models may be appropriate for data with more persistent noise, we assume that short-term fluctuations dominate the variability in our data.

We use an ARMA(1,1) model for our analysis. This incorporates both the autoregressive and moving average terms and is consistent with the principle of parsimony, stating that generally one should prefer simpler models over more complex models that can also be used for adequate data explanation. The idea is that we generally prefer simpler models because they are easier to understand, interpret, and statistically apply.

We further elaborate our study by including renewable generation as an exogenous variable (following Knittel and Roberts, 2005; Rintämaki et al., 2017; Mauritzen, 2010; Weron and Misiorek, 2008). We do so by setting up an ARMAX model. The resulting model ($p, q, b$) adds $b$ exogenous variables to the described ARMA model. The $b$ term is a linear combination of a known and external time series $d_t$.

Adding the exogenous variable allows us to examine the relationship between renewable energy generation and electricity prices while accounting for any autocorrelation or moving average effects present in the data. By including renewable energy generation as an exogenous variable in our ARMAX model, we can gain insight into how this variable affects our dependent variable over time.

*Volatility models*

Our study aims to see how electricity price volatility has been affected over time by demand shocks, supply shocks, and renewable energy generation over the past five years.

Following, among others, Rintämaki et al. (2017) and Mauritzen (2010), we compute our primary measure of price volatility for day $d$ from daily average prices $p_d$ and weekly average prices $P_w = \frac{1}{7}\sum_{d=1}^{7} P_d$.

Consequently, we calculate volatility as the standard deviation of prices:

$$v_w = \sqrt{\frac{1}{7}\sum_{d=1}^{7}(P_d - P_w)^2} \tag{6}$$

To see how volatility is affected in the three time periods, we run the same ARMA(X) regressions as for the price series. We now define the dependent variable and its lagged term as the standard deviation of electricity prices. This allows us to find the influence of last week's price volatility and renewable energy generation on this week's price volatility.

# 6. Results

The results section presents the findings of the study, highlighting the outcomes of the data analysis and answering the stated hypotheses. We provide an objective and comprehensive overview of the analyzed data, detailing the key findings and their significance.
First, we analyze the findings for our price models, whereafter we discuss the volatility models' results. We end the section with model extensions and the testing of significant coefficient differences.

## 6.1 Price models

To gauge the predictive power of prices, we use specification (7):

$$P_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 \varepsilon_{t-1} + \varepsilon_t \tag{7}$$

Where $P_t$ is the electricity price at time $t$ and $\varepsilon_t$ is the white noise error term. Table 5 shows the estimation results for the ARMA(1,1) model with price as the dependent variable. We can see throughout our sample periods that the lagged price coefficient is highly significant. For the full sample, the coefficient of nearly 0.93 indicates a strong dependency for prices on their lagged terms. We can see that over our periods this dependency drops. Most noticeable is how during the later stage of the pandemic and during war times, the coefficient drops by around twenty percent compared to its values in the first two periods. We can conclude that during the steep demand increase in the post-COVID-19 period and the unpredictability of supply during the war, prices from one period earlier carry less explanatory power than before. It is interesting though, that during the period of low demand lagged prices seem to hold relatively much explanatory power, regardless of the uncertainty caused by COVID-19 and the government's measures.
Past periods' error terms do not hold much significant explanatory power. For the full sample, past error terms do improve electricity price forecasting. This may be due to the sample size being larger than for the individual samples. Further, lagged errors influenced prices during the first pandemic period. We find a negative relation between past residuals and current prices. If there was more randomness for our model in the previous period, i.e., lagged prices held less explanatory power, current prices decrease. This finding suggests that the model may not fully

capture the underlying factors of current price movements. This finding is not surprising, as we only use lagged prices and error terms as explanatory variables.

The sigma parameter represents the standard deviation of the model's error term. Essentially, it measures how well the model fits the data, with smaller values indicating a better fit. We find that the first pandemic period fits our model best out of the three specified time periods after the base case.

Table 5: Estimation Results for ARMA(1,1) Price Regression

| | Full sample | Base case | Pandemic 1 | Pandemic 2 | War |
|---|---|---|---|---|---|
| $P_{t-1}$ | 0.926*** | 0.948*** | 0.989*** | 0.695** | 0.748*** |
| | (0.024) | (0.038) | (0.024) | (0.321) | (0.123) |
| $\varepsilon_{t-1}$ | 0.139*** | -0.325 | -0.227* | 0.692 | 0.262 |
| | (0.037) | (0.073) | (0.117) | (0.435) | (0.180) |
| $Sigma$ | 31.153*** | 4.500*** | 6.171*** | 26.333*** | 58.255*** |
| | (0.573) | (0.223) | (0.456) | (4.868) | (5.349) |
| Constant | 89.532 | 44.030*** | 62.798** | 194.810*** | 221.863*** |
| | (62.000) | (6.012) | (31.863) | (42.974) | (44.528) |
| Observations | 261 | 104 | 88 | 16 | 53 |

***=1% significance, ** = 5%, *=10%, robust standard errors are found in brackets

We add renewables to our price model. The corresponding ARMAX(1,1,1) is given in specification (8). Note that for renewable electricity generation we take the sum of offshore wind, onshore wind, and Solar PV. From the literature, we expect all three variables to have a negative effect on prices, hence aggregating them is appropriate.

$$P_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 \varepsilon_{t-1} + \beta_3 R_t + \varepsilon_t \tag{8}$$

Where $R_t$ represents renewable electricity generation. We present the results for the price model in Table 6. We can see that for every sample set of our study, adding renewables generation data adds explanatory power to our price model at the 1% significance level.

The negative coefficients for the renewables variable show that the day-ahead price decreases with the generation of renewable energy. This confirms findings by Jónsson et al., (2010), Ketterer (2014), Forrest and MacGill (2013), and Brancucci Martinez-Anido et al., (2016) among others. Noticeable is how strongly its influence rises over our sample periods. During the pandemic period of fallen demand, we see a relatively small increase in the coefficient for renewables. Subsequently, the coefficient increases by a factor four and seven, respectively, indicating a significant increase in the influence of renewables on prices. We see that the coefficient surpasses the value of -1, so its effect on prices is larger than the added capacity. In line with the literature, prices during periods of high demand tend to be influenced more strongly by renewable generation due to their low variable costs. Moreover, we find the same effect during periods of low supply. Renewable electricity generation has consistently grown over the years, making their share in the electricity grid larger, assuming no change in the quantities of demand and supply. We confirm the finding that when renewable electricity has a significant (rising) share in the generation portfolio, substantial short-term changes in the supply function arise from variations in renewables generation (Jónsson et al., 2010).

The market has experienced surging prices during the Russian-Ukrainian conflict. The restricted energy supply, bombing of critical infrastructure and besiegement and sabotage of energy assets all made energy supply both smaller and more uncertain in its output. Electricity supplied by renewables in such times is relatively more certain than it is typically. This effect, coupled with the growing output of renewable electricity could, to some extent, explain the rise in renewables' regressed coefficient.

Again, we find a relatively low sigma for the first pandemic period.

Table 6: Estimation Results for ARMAX(1,1,1) Price Regression

| | Full sample | Base case | Pandemic 1 | Pandemic 2 | War |
|---|---|---|---|---|---|
| $P_{t-1}$ | 0.944*** | 0.949*** | 0.988*** | 0.951*** | 0.696*** |
| | (0.018) | (0.041) | (0.274) | (0.193) | (0.131) |
| $\varepsilon_{t-1}$ | 0.149*** | -0.300*** | 0.0732 | 0.537 | 0.432* |
| | (0.038) | (0.061) | (0.100) | (0.332) | (0.227) |
| $R_t$ | -0.925*** | -0.192*** | -0.239*** | -1.044*** | -1.840*** |
| | (0.100) | (0.060) | (0.029) | (0.214) | (0.318) |
| $Sigma$ | 27.739*** | 4.303 | 4.799*** | 17.630*** | 45.570*** |
| | (0.681) | (0.209) | (0.368) | (3.952) | (3.796) |
| Constant | 116.998* | 47.52*** | 70.660** | 239.742*** | 302.925*** |
| | (63.027) | (6.387) | (32.239) | (80.522) | (40.073) |
| Observations | 261 | 104 | 88 | 16 | 53 |

***=1% significance, ** = 5%, *=10%, robust standard errors are found in brackets

## 6.2 Volatility models

To gauge the effects of our volatility model, specification (9) is used. Note that renewables generation is the sum of offshore wind, onshore wind, and solar power. From the literature, we expect solar PV to exhibit a negative relationship with price volatility and wind generation to exhibit a positive one. As is shown earlier, solar power likely increases volatility during hours of high demand (Clò et al., 2015). During these peak hours, the total electricity supply goes up. Peak hours smooth out over daily averages, since there is no distinction between peak- and off-peak hours. Going one step further and aggregating these daily values to weekly values fortifies this effect. We assume that when looking at weekly volatility, solar and wind both exhibit a positive effect on volatility, hence aggregating them as a single variable does not change the inferences made.

$$v_t = \beta_0 + \beta_1 v_{t-1} + \beta_2 \varepsilon_{t-1} + \varepsilon_t \tag{9}$$

Table 7 reports the regression results for our ARMA(1,1) volatility model. For the full sample, we find that lagged volatility and the model's lagged error term add significant explanatory power to this period's price volatility. The coefficient of lagged weekly volatility approaches a value of 1, indicating the high explanatory value past volatility holds in our model. The past period's error term negatively effects this period's price volatility, meaning that when our model yields a better prediction at time $t$, it finds more volatility in period $t + 1$. A possible explanation is that unexpected events or changes in the market are not fully captured by the model, leading to higher price volatility in the current period.

For the base case no significant results are found, which makes comparisons to this time period insignificant. In our sample, lagged volatility does not explain volatility for the next period.

Again, we find significant results and a relatively low sigma for the first pandemic period. Lagged volatility has a coefficient of over 0.7, significant at the 1% level. Clearly, in this period volatility can partly be explained by past week's volatility.

The second pandemic period yields a value of precisely -1 for the lagged error term. In other words, when the error term was larger in the previous period, volatility in the current period is smaller by the same magnitude.

We find significant results for the war period. Volatility is explained well by both lagged volatility values and the error term.

From these results, we conclude that when volatility increases, either due to distortions in demand or supply, looking at past price volatility can partly explain volatility in the next period.

Table 7: Estimation Results for ARMA(1,1) Volatility Regression

| | Full sample | Base case | Pandemic 1 | Pandemic 2 | War |
|---|---|---|---|---|---|
| $v_{t-1}$ | 0.971*** | 0.167 | 0.727*** | 0.851 | 0.757*** |
| | (0.016) | (0.517) | (0.186) | (0.676) | (0.172) |
| $\varepsilon_{t-1}$ | -0.675*** | 0.024 | -0.412* | -1.00** | -0.498** |
| | (0.032) | (0.531) | (0.246) | (0.443) | (0.226) |
| $Sigma$ | 14.099*** | 2.293*** | 4.751*** | 20.05$^{\Psi}$ | 27.010*** |
| | (0.276) | (0.128) | (0.318) | | (2.520) |
| Constant | 17.551 | 4.807*** | 7.931*** | 30.325*** | 46.372*** |
| | (18.495) | (0.357) | (1.447) | (7.834) | (11.479) |
| Observations | 261 | 104 | 88 | 16 | 53 |

***=1% significance, ** = 5%, *=10%, robust standard errors are found in brackets

The corresponding ARMAX(1,1,1) is given by:

$$v_t = \beta_0 + \beta_1 v_{t-1} + \beta_2 \varepsilon_{t-1} + \beta_3 R_t + \varepsilon_t \tag{10}$$

Table 8 shows the results of our volatility model, including renewable energy generation as an explanatory variable. Adding renewable generation adds little explanatory power to our model. Again, the first pandemic period fits the model best and yields a significant coefficient for renewable generation. To some extent, renewable energy generation explains volatility within the period. Moreover, lagged prices and error terms hold explanatory power to price volatility in the period.

We can model electricity price volatility during the war by using lagged volatility and the lagged error term.

Interestingly, no significant coefficient for renewable electricity generation is found in the base case. This result suggests that weekly price volatility is not explained by renewable electricity generation. Though the literature is not conclusive on the effects of renewables on volatility, we would expect volatility to increase when renewable electricity is added to the grid. This is due to the relatively large share of wind power in the Netherlands, which would increase

$\Psi$ No standard error, P-value, or confidence interval found volatility (e.g., Clò et al., 2015; Woo et al., 2011; Jónsson et al., 2010). Our results cannot confirm this expectation. It is possible that mean electricity prices are considerably reduced with the addition of renewable electricity, which in turn reduces their volatility, in line with findings of Brancucci Martinez-Anido et al. (2016) and Gelabert et al. (2011). Note that this is the case when not distinguishing between peak- and non-peak hours.

Table 8: Estimation Results for ARMAX(1,1,1) Volatility Regression

| | Full sample | Base case | Pandemic 1 | Pandemic 2 | War |
|---|---|---|---|---|---|
| $v_{t-1}$ | 0.965*** | 0.165 | 0.752*** | 0.558 | 0.766*** |
| | (0.185) | (0.547) | (0.141) | (1.040) | (0.165) |
| $\varepsilon_{t-1}$ | -0.656*** | 0.027 | -0.406** | -0.100 | -0.479** |
| | (0.034) | (0.561) | (0.201) | (2071.449) | (0.227) |
| $R_t$ | 0.119 | 0.003 | 0.075** | 0.421 | 0.152 |
| | (0.078) | (0.038) | (0.037) | (0.667) | (0.362) |
| $Sigma$ | 14.027*** | 2.293*** | 4.645*** | 18.799 | 26.890*** |
| | (0.304) | (0.130) | (0.296) | (19466.9) | (2.975) |
| Constant | 13.868 | 4.762*** | 5.601** | 12.516 | 40.192** |
| | (16.680) | (0.746) | (2.391) | (25.752) | (16.420) |
| Observations | 261 | 104 | 88 | 16 | 53 |

***=1% significance, ** = 5%, *=10%, robust standard errors are found in brackets

The significant values observed for the lagged error terms in our models lead us to draw two conclusions. First, including the lagged error term as a predictor in ARMA(X) models improves the accuracy of both electricity price and volatility forecasts. The error term captures randomness in the variables that is not accounted for by the model. By including the lagged error term, we are learning from past errors and using this information to improve the model's accuracy. Second, analyzing the relation between past error terms and current electricity prices and their volatility can provide insight into underlying drivers of price movements and volatility in the electricity market. Say that one finds the error terms to correlate with other factors (e.g., oil prices, wind velocity, or the closing of coal-fired generators), extensions to the models described in this study could be identified.

### 6.3 Model extensions

We ran the regressions with separated values for wind- and solar generation to see whether this yielded significance for their coefficients. The resulting models did not yield significance for the exogenous variables. We conclude that relaxing our assumption of aggregated renewable generation sources does not add explanatory power to our models.

We must acknowledge that price volatility is influenced not only by the supply side, but demand plays an important role too. We know that in winter months, demand is greater than in summer months (e.g., Hekkenberg, Benders, Moll and Schoot Uiterkamp 2009). The literature suggests that when demand is lower, electricity facilities can manage it well, so renewables' influence on volatility is weaker than during periods of high demand. Higher demand leads to the addition of active generators to match it. This, coupled with their convex marginal cost structure, results in higher price volatility (Mwampashi et al., 2021). We extend our model with a dummy variable that takes on the value of 1 for the months of December, January, and February to investigate whether, during winter, renewables generation yields a significant effect on volatility. We add the term in our volatility models as an exogenous variable resulting in the following specification:

$$v_t = \beta_0 + \beta_1 v_{t-1} + \beta_2 \varepsilon_{t-1} + \beta_3 R_t + \beta_4 W + \varepsilon_t \tag{11}$$

The results for the corresponding models are found in Appendix 3. Adding the winter dummy variable yields insignificant results for all of our samples. The higher output levels of renewables during winter months could explain this finding. Recent literature suggests that similar periods of high demand in the Netherlands occur more often in summer due to the rising temperatures and hence the increased use of air conditions and other devices. Adding the summer dummy for the months of June, July, and August does not add explanatory power either.

We also added the winter dummy to our price regression. Its results are found Appendix 4. Only for the base case, this leads to a significant result at the 1% level. The negative value of nearly -5 for the winter dummy indicates that prices during winter weeks are lower on average. This contradicts our expectations but it is possible. We have seen that during the winter months, renewable electricity output in the Netherlands is relatively high. This, in turn, expands supply and could result in negative pressure on prices. Another possible explanation could be that during the winter months of 2018 and 2019, prices of other fuel types were relatively low, influencing electricity prices indirectly.

We conclude that weekly price volatility over the last five years as a whole and during the specified periods cannot be (partially) explained by renewable electricity generation, except in the first pandemic period. Looking at periods of high- versus low demand does not add explanatory power to its coefficient.
The events of the last five years may have distorted the market in a way that overshadows the effects the literature suggested we would find. Noticeable is how during the base case, no significant effect is found. There are likely other factors that dissipate the effect we expected to find for the years 2018 and 2019. A possible explanation is that the addition of renewable electricity considerably reduces the mean of electricity prices, which reduces their volatility.

### 6.4 Statistical differences coefficients

Having estimated our models for two different samples, we obtained the coefficients of the renewable energy variable. To answer whether this influence was larger during our sample periods compared to the base case, we must investigate whether the coefficients between the samples are significantly different from each other. The t-value of the difference measures the difference between two coefficients relative to their standard error, and is used to test whether the difference is statistically significant. In this section, we present the results of the tests and discuss their implications for the stated hypotheses.

We define the difference between two coefficients as:

$$x_i = c_1 - c_2 \tag{12}$$

Then the standard error of the difference is given by:

$$se_x = \sqrt{(se_1)^2 + (se_2)^2} \tag{13}$$

Consequently, the t-value of the difference is given by:

$$t_i = \frac{x}{se_x} \tag{14}$$

We define the corresponding significance with degrees of freedom $df = n_1 + n_2 - 2$, except for the second pandemic period. Since the $n$ is relatively small compared to the sample sizes of the others periods, we use a more robust degree of freedom of $df = 16 - 2 = 14$.

We test the null hypothesis that our coefficients are equal with a one-sided test. We perform a one-sided test since we stated directional hypotheses. For example, hypothesis 4 states that the coefficient for renewable electricity generation in the price model for the pandemic period is larger than its coefficient in the base case.

Table 9 presents an overview of the differences between coefficients, the corresponding standard errors, and the significance levels of the differences. Please note that the periods are compared against the base case, as stated in our hypotheses. For the price model without renewable electricity generation, we find a significant coefficient of the difference between the coefficients of lagged prices during the war and lagged prices of the base case. Though we find significant coefficients for the variable among the different samples, we conclude that, statistically, the influence of lagged prices is larger in the base case than in the war period. This paper finds that during times of war (supply chain distortions), the predictability of weekly prices by their lagged values is lower than during "normal" times. The results of the price model including renewables confirm this finding.

The values for the price model including renewables yield significant results for two periods. From Table 6, we know that the coefficients of renewables were more negative for the last two periods of the study. The results presented below provide evidence that during the recovery period of the pandemic and during the war, the impact of renewable electricity generation on prices is larger than in the base case. The magnitude of the effect during the war is the largest, with a value of 1.648, nearly twice the magnitude for the second pandemic period. We can see that, though not significant, comparing the first pandemic period and the base case yields a minor difference in coefficients when adding renewables.

Table 9: Coefficient Differences Compared to Base Case Price Regression

| | ARMA(1,1) | ARMAX(1,1,1) |
|---|---|---|
| $P_{t-1}$ Pandemic 1 | -0.041 | -0.039 |
| | (0.045) | (0.277) |
| $P_{t-1}$ Pandemic 2 | 0.253 | -0.002 |
| | (0.323) | (0.197) |
| $P_{t-1}$ War | 0.200* | 0.253** |
| | (0.129) | (0.137) |
| $R_t$ Pandemic 1 | | 0.047 |
| | | (0.067) |
| $R_t$ Pandemic 2 | | 0.852*** |
| | | (0.222) |
| $R_t$ War | | 1.648*** |
| | | 0.324) |

***=1% significance, ** = 5%, *=10%, standard errors of the difference are found in brackets

Table 10 presents an overview of the differences between coefficients for the volatility models. We find no significance for the coefficient differences. We do see negative difference coefficients in values ranging between -0.5 and -0.7 for our first model. We know that during the first pandemic period and the war, coefficients for lagged volatility are significant. These findings suggest that the effect of lagged volatility on weekly volatility is likely larger in periods with more price volatility.

For the volatility model including renewables, we again find negative coefficient differences. This finding suggests that during these periods, it is likely that renewable electricity generation has a more significant effect on price volatility, though we cannot confirm this statistically.

Table 10: Coefficient Differences Compared to Base Case Volatility Regression

| | ARMA(1,1) | ARMAX(1,1,1) |
|---|---|---|
| $v_{t-1}$ Pandemic 1 | -0.560 | -0.587 |
| | (0.549) | (0.565) |
| $v_{t-1}$ Pandemic 2 | -0.684 | -0.393 |
| | (0.851) | (1.175) |
| $v_{t-1}$ War | -0.590 | -0.601 |
| | (0.545) | (0.571) |
| $R_t$ Pandemic 1 | | -0.072 |
| | | (0.053) |
| $R_t$ Pandemic 2 | | -0.418 |
| | | (0.668) |
| $R_t$ War | | -0.149 |
| | | (0.364) |

***=1% significance, ** = 5%, *=10%, standard errors of the difference are found in brackets

Appendix 5 presents an overview of the hypotheses studied in this paper, indicating whether our study provides evidence to confirm them and at what significance level.

## 7. Conclusion and implications

*Conclusion*

The scope of this paper is to review how the influence of renewable electricity generation evolved over times of fallen demand and supply chain distortions. By using ARMA and ARMAX models, we have assessed whether renewables influenced Dutch day-ahead prices and their volatility during uncertain times and compared the outcomes against an up-to-date base case.

We conclude that for every sample, lagged weekly prices hold explanatory power for electricity prices. Further, renewable electricity generation can partly explain price movements. We have found that prices decrease with the addition of renewables in the grid. As a result, we confirm the merit order effect for our sample. We found that in our model, this negative relationship has grown stronger over the past five years. Consequently, we tested whether the coefficients significantly differ compared to our base case. Past price values better explained prices during the war compared to the base case. Further, during the recovery period after the COVID-19 pandemic and the period of war, the merit order effect in the Netherlands is stronger. Not only periods of high demand are affected more strongly, but the same holds for periods of low supply in even greater magnitude. Electricity supplied by renewables in times of low, uncertain supply is relatively more certain than it is typically. This effect, coupled with the growing output of renewable electricity could, to some extent, explain this finding. Distinguishing periods of high demand (winter months) yielded significant results for our price model, strengthening our results. Ultimately, we conclude that periods of high demand and periods of low supply are affected most significantly by the addition on renewable electricity to the grid.

We followed by estimating our volatility models. For the first pandemic period and the war, we found that lagged volatility values hold explanatory power over weekly electricity price volatility. Adding renewable electricity generation to our model yielded a significant coefficient for the first pandemic period only. This relationship was positive, meaning that with the addition of renewable electricity to the grid, volatility increased during the first pandemic period. However, during our base case, high demand, and low supply periods, renewable electricity generation does not influence weekly price volatility. A possible explanation for this finding is that with the addition of renewable electricity generation, mean prices are considerably reduced, in turn reducing their volatility. Also, our model extensions, controlling for periods of high demand (winter months) or separating solar and wind, did not yield significant results for the renewables variable. We continued by testing the differences between the coefficients against the base case, but this yielded no significant results. The resulting values are all negative, suggesting that it is likely that renewable electricity generation has a more significant effect on price volatility when moving up over our samples.

*Implications*

The findings of this paper provide insights into how renewable electricity generation influences prices.

The extrapolation of our findings can yield valuable insights into the behavior of electricity prices and their volatility in times of uncertainty. It is well established that the first phase of the pandemic experienced a decline in demand and heightened uncertainty regarding its future growth trajectories. Conversely, the second pandemic period witnessed strongly growing demand and a corresponding rebound effect. The outcomes observed during the war can have relevance to the event of supply chain disruptions, which may arise during similar events in the future. A note here is that the Russian-Ukrainian conflict has had an unprecedently large impact on the energy supply chain. Extrapolation of these results should therefore be done carefully.

Risk- and asset-pricing managers have already factored in the pandemic and the Russian-Ukrainian conflict in their short and medium-term decision-making process for the development of business plans. This study provides particularly insightful considerations for energy companies that are affected substantially by fluctuations in energy prices. It is evident that, in times of uncertainty, the integration of renewable energy into the electricity grid has a more adverse effect on electricity prices, resulting in a combination of uncertainty in supply and decreasing prices. Especially for conventional energy producers, it is critical to have a contingency plan in place to handle similar events in the future. Meanwhile, individual investors must also consider COVID-19 and supply chain uncertainty in their investment agendas. Further, integrating more renewables in the grid may result in conventional power plants serving more in the role of balancer for fluctuations in renewable generation and therefore operating fewer full-load hours. As a consequence, recovering the investment costs for flexible conventional units during operating hours will become more challenging. The peak-price periods will be the revenue-generating hours, but the predictability and certainty of these hours may decline with the addition of renewable power. The increased refinancing risk described here raises concerns about the feasibility of investing in flexible (conventional) plants, and the market price may not provide sufficient investment opportunities.

This study highlights the importance of necessitating appropriate regulatory- and policy frameworks to address the challenges arising from further decarbonization of the electricity market. One of the key challenges is to manage price uncertainty, as the high penetration of wind and solar generation potentially threatens the system’s security and reliability. For policymakers it is equally important to update pricing models, especially for the determination of long-term subsidy schemes. We expect subsidies to continue to play a crucial role in mitigating payment deficiencies throughout the transition period and potentially beyond. For example, policies should consider the potential divergence of spot prices in the design of subsidy policies (such as contract-for-difference reference prices) as renewable capacity expands. We provide estimations on how renewable generation's impact depends on varying market characteristics which are useful for updating pricing- and subsidy models. Finally, our findings demonstrate that the impact of renewables on reducing electricity prices is particularly significant during periods where end-consumers are adversely affected by high prices. Policymakers must meticulously balance the impacts on operators, consumers and the environment and form their policies accordingly.

## 8. Limitations and further research

*Limitations*

This paper aims to improve the existing knowledge and provide quantified results for the impact of renewables on electricity prices and their volatility. We must acknowledge some factors limit our research and its findings.

First, even though this study argues its choice of using weekly aggregated data, we must recognize its impact on our findings. The use of weekly data smooths out effects over periods, especially the variability of both electricity prices and renewable electricity generation. The use of data at smaller intervals may yield significant results for the volatility models. We recommend carefully considering the selection of input data to ensure that it is optimally suitable for answering the research question.

Second, this study uses weekly price data gathered for 24-hour periods of a day, calculated as its arithmetic mean. Basic economic theory tells us that with higher prices, lower quantities are sold per hour, which also holds in the day-ahead auction process. Hence, by not using the geometric mean, our daily prices may contain an upwards bias. This would result in overestimation of our regression coefficients. We assume this influence to be relatively small, especially given the inelasticity of electricity demand, but it is a limitation nonetheless. Let us explain this in more detail. In the electricity market, short-term demand is assumed inelastic, so one could argue that daily demand is given. Because of the hourly intersections of demand and supply, no significant difference is expected by comparing arithmetic and geometric daily means. Though since electricity cannot be stored, hourly prices can differ significantly. This means that with high prices, buyers may postpone the purchase of electricity, since they have the option to balance out the amount of electricity in the intraday market. Postponing purchase poses a risk for market players since the intraday market sells at a premium. Hence, we assume the potential overestimations to be small, but they should still be mentioned.

Lastly, we aggregate the effects of COVID-19 by setting the time periods as outlined. We performed a structural break test, splitting the pandemic period into a period of fallen demand and a recovery period. The recovery period, with a small sample size, likely defines the period of rising demand relatively well without including many other fluctuations in the market or regulatory field. Meanwhile, the first pandemic period is more prone to the inclusion of other such factors. When aiming to gain a deeper understanding of how exactly the pandemic affected electricity prices and the influence of renewables over time, it may be prudent to split the pandemic period up in more detail. Such a study may find more significant results for periods with less restrictive measures compared to lockdown periods.

*Further research*

This study provides a foundation for studying electricity price dynamics over different periods. Further research could extend the findings of this paper in multiple ways.

First, this study investigated price patterns over time in a robust method, using only two variables. Further advanced models could improve our results by capturing aspects which our models do not fully explain. Variables that future studies could incorporate are for instance (variability in) wind velocity or sunshine, oil price movements, or the closing of coal-fired generators. One could identify variables of interest by finding correlations between our models' error terms and potential variables. Second, extending this research with daily or hourly data to study the short-term implications of renewables on prices and their volatility provides insights into the short-term dynamics of the electricity market. Further, to enhance our knowledge of electricity price behavior during the pandemic looking into the price dynamics of more detailed periods is interesting. Such a study could, for instance, define periods by looking at strict lockdowns, partial lockdowns, and no-lockdown restrictive measures and compare these against a base case. Lastly, this study confirms the merit order effect, where adding renewable electricity sources lowers prices. Suppose the government will not subsidize all of the investment costs for renewables, and renewables make up the largest part of power generation, then where does this merit order effect come to a halt? Looking into this question would provide interesting findings for governments, market participants, investors and end-consumers.

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# APPENDIX

## A1: Variable Table

| Variable | Description |
|---|---|
| $P_t$ | Dutch day-ahead APX electricity price in period $t$. Daily and values are collected, calculated as arithmetic means of 24-hour periods. Price is measured in euro per megawatt hour. |
| $R_t$ | Renewable electricity generation in the Netherlands in period $t$. Values are aggregated values of offshore wind, onshore wind, and solar PV. Renewables are measured in megawatt. |
| $v_t$ | Volatility in time period $t$. Volatility is calculated as the standard deviation of electricity prices. |
| $W$ | The dummy variable for winter weeks. The dummy variable equals 1 for weeks of December, January, and February, and 0 otherwise. |
| *Base case* | The reference period used in this study. The period ranges from 01/01/2018 – 31/12/2019. |
| *Pandemic 1* | The first pandemic period, representing a time of fallen demand for electricity due to restrictive measures. The period ranges from 01/01/2020 – 05/09/2021. |
| *Pandemic 2* | The second pandemic period, representing a time of recovery and rising demand for electricity. The period ranges from 06/09/2021 – 31/12/2022. |
| *War* | The period representing energy supply chain distortions due to the Russian-Ukrainian geopolitical conflict. Takes into account anticipation effects of January and early February 2022. The period ranges from 01/01/2022 – 31/12/2022. |

A2: Attempted Tests Criteria

| **Test** | **Criteria not met** |
|---|---|
| T-test | • Random sampling<br>• Normally distributed data<br>• Homogeneity of variances |
| Wilcoxon rank-sum test | • Normally distributed populations |
| Kruskal-Wallis test | • Random sampling<br>• Independence among observations |
| One-way ANOVA | • Normal distribution<br>• Independence among observations |
| Repeated measures ANOVA | • Normal distribution<br>• Independence among observations |
| Friedman test | • Random sampling |
| Mixed effects model | • Normally distributed errors<br>• Independence among errors |

A3: Estimation Results Volatility Model Including Winter Dummy

| | Full sample | Base case | Pandemic 1 | Pandemic 2 | War |
|---|---|---|---|---|---|
| $v_{t-1}$ | 0.965*** | 0.198 | 0.641*** | 0.171 | 0.735*** |
| | (0.019) | (0.647) | (0.214) | (0.759) | (0.200) |
| $\varepsilon_{t-1}$ | -0.656*** | -0.002 | -0.307 | -1.00 | -0.462* |
| | (0.034) | (0.662) | (0.278) | (4059.468) | (0.257) |
| $R_t$ | 0.119 | 0.011 | 0.084** | 0.371 | 0.175 |
| | (0.078) | (0.038) | (0.038) | (0.477) | (0.389) |
| $W$ | -0.199 | -0.498 | -2.800 | 14.897 | -9.922 |
| | (0.078) | (0.688) | (2.378) | (0.477) | (19.606) |
| $Sigma$ | 14.027 | 2.287*** | 4.606*** | 14.690 | 26.770*** |
| | (0.304) | (0.130) | (0.323) | (29817.56) | (3.002) |
| Constant | 13.920 | 4.728*** | 6.011*** | 11.250 | 42.309** |
| | (16.82) | (0.746) | (2.200) | (19.113) | (16.528) |
| Observations | 261 | 104 | 88 | 16 | 53 |

***=1% significance, ** = 5%, *=10%, robust standard errors are found in brackets

A4: Estimation Results Price Model Including Winter Dummy

| | Full sample | Base case | Pandemic 1 | Pandemic 2 | War |
|---|---|---|---|---|---|
| $P_{t-1}$ | 0.945*** | 0.946*** | 0.990*** | 0.967*** | 0.703*** |
| | (0.0178) | (0.041) | (0.259) | (0.158) | (0.129) |
| $\varepsilon_{t-1}$ | 0.147*** | -0.263*** | 0.034 | -465.036 | 0.437** |
| | (0.037) | (0.080) | (0.102) | (77309.02) | (0.222) |
| $R_t$ | -0.939*** | -0.185*** | -2.50*** | -1.207*** | -1.828*** |
| | (0.101) | (0.057) | (0.030) | (0.290) | (0.316) |
| $W$ | 11.679 | -4.948*** | 5.211 | 23.615 | 14.378 |
| | (7.576) | (1.355) | (5.207) | (144.234) | (38.509) |
| $Sigma$ | 27.647*** | 4.188*** | 4.706*** | -0.043 | 45.467*** |
| | (0.673) | (0.230) | (0.356) | (7.222) | (3.820) |
| Constant | 113.634* | 49.505*** | 69.921** | 236.012*** | 297.686*** |
| | (61.160) | (6.648) | (33.943) | (84.112) | (45.042) |
| Observations | 261 | 104 | 88 | 16 | 53 |

***=1% significance, ** = 5%, *=10%, robust standard errors are found in brackets

A5: Overview of Hypothesis Outcomes

| Hypothesis | Verified (Yes/No) | Significance level |
|---|---|---|
| $H1_1$ | Yes | 1% |
| $H2_1$ | No | |
| $H3_1$ | Yes | *n/a* |
| $H4_{1.1}$[5] | No | |
| $H4_{1.2}$ | Yes | 1% |
| $H5_1$ | No | |
| $H6_1$ | Yes | *n/a* |
| $H7_1$ | Yes | 1% |
| $H8_1$ | No | |

[5] Where 1.1 represents the first pandemic periods and 1.2 represents the second pandemic period