

Essays in Environmental and Energy Economics

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ABSTRACT

This dissertation focuses on issues related to the climate change crisis that we are facing today, using tools in environmental and energy economics. Papers of this dissertation analyze decarbonization of the electricity generation, supply responses of fossil fuels to price changes, and the impact of carbon taxes on corporate performance. The first paper examines the impact of a rapid increase in renewable energy share on the electricity market outcomes using the negative demand shock during the COVID-19 pandemic. The negative demand shock and the increase in renewable energy share in the electricity grid attenuate wind energy's impact on reducing electricity generation from natural gas and amplifies its effect on reducing electricity generation from coal and lignite. The negative demand shock also attenuates wind energy's ability to reduce short-term electricity prices compared to the regular demand period. Regarding climate impacts, electricity from wind energy reduced marginal GHG emissions during periods of reduced electricity demand at a higher rate than the regular electricity demand period. The second paper examines how conventional and unconventional well operators respond to oil price volatility in the extraction stage of oil production. Findings show that in unconventional wells, oil production does not respond to oil price increases and decreases in symmetric magnitudes. On the other hand, oil production in conventional wells does not respond to oil price changes. The third paper analyzes the effect of the change in the anticipated trajectory of French carbon tax rates on French manufacturing firms' equity performance. Findings indicate that stock prices of firms operating in energy intensive sectors exhibited excess positive returns in response to the carbon tax rate suspension. In contrast, firms in less energy intensive sectors had excess negative returns. Furthermore, robustness checks verify the unexpected nature of the announcement and affirm that investors did not under or over-react to the announcement and excess returns were maintained in the days following the event.

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Chapter 1

INTRODUCTION

This dissertation focuses on issues related to the climate change crisis that we are facing today, using tools in environmental and energy economics. In the three papers of this dissertation, I analyze decarbonization of the electricity generation, fossil fuel supply responses to price changes and the impact of carbon taxes on corporate performance.

In the first paper, I examine the impact of a rapid increase in renewable energy share on the electricity grid and decarbonization prospects. As ambitious climate pledges aim to decrease fossil fuel use in electricity generation, the implications of integrating growing intermittent renewable energy capacity in electricity grids become an imminent issue for grid operators and policy makers. However, causally identifying the effects of a rapid increase in renewable energy share is challenging. The negative electricity demand shock during the COVID-19 lockdowns increased the share of zero-marginal cost renewable energy in the electricity generation mix. I use this unique demand shock to examine how a higher share of renewable energy impacts the electricity generation from fossil fuels, merit-order (short-term price) effect, GHG emissions and damages from fossil fuel combustion in electricity generation. To derive my inferences, I use Turkey's hourly electricity generation data by fuel and generator type, aggregate electricity demand, and GHG emissions at the power plant level. I find that wind energy reduces electricity generation from fossil fuel power plants during and before the negative demand shock. However, the negative demand shock attenuates wind energy's impact on reducing electricity generation from natural gas and amplifies its effect on reducing electricity generation from coal and lignite. The negative demand shock also attenuates wind energy's ability

to reduce short-term electricity prices compared to the regular demand period. Regarding climate impacts, electricity from wind energy reduced marginal GHG emissions during periods of reduced electricity demand at a higher rate than the regular electricity demand period. An additional MWh of wind energy during the negative electricity demand shock period reduced \$24.17, \$8.82 and \$33.92 worth of damages from CO₂, CH₄ and N₂O emissions, respectively. The analysis in this chapter could inform policy makers by showing that even in low environmental regulation contexts, policies that boost the installed capacity for renewable energy might be a powerful tool in climate change mitigation.

In the second paper, I focus on the determinants of fossil fuel supply in response to oil price changes. Understanding how oil producers respond to fluctuations in oil prices is often of great interest to policymakers in designing environmental policies and reducing volatility in energy markets. In this paper, with my co-author Michi Toya, we investigate whether asymmetries exist in supply responses to increases and decreases in oil prices. Using monthly well-level data extending from January 1990 to December 2021 from North Dakota, we examine how operators of conventional and unconventional wells respond to oil price volatility in the extraction stage of oil production. Findings show that in unconventional wells, oil production does not respond to oil price increases and decreases in symmetric magnitudes. A 1% price increase in oil prices is associated with 0.022% increase in contemporaneous oil production in unconventional wells and a 1% decrease in oil prices is associated with a 0.08% decrease in contemporaneous oil production. The difference between these two supply elasticities is also statistically significant. On the other hand, oil production in conventional wells do not respond to oil price changes. The existence of these asymmetries in production responses to oil prices indicates that previous estimates of price elasticity of supply for oil might be misleading if treated as bidirectional. The main contribution of this paper is that it

shifts the focus from asymmetric price elasticity of energy demand to energy supply and extends previous literature on the price elasticity of oil supply.

In the third paper, I assess the impact of an environmental policy shock on firms' corporate performance proxied by their equity market performance. Particularly, I analyze the effect of the change in the anticipated trajectory of French carbon tax rates on French manufacturing firms' equity performance. I exploit the unexpected announcement to suspend the French carbon tax increase due to Yellow Vests protests at the end of 2018 as an event altering the expectations of investors on climate policy stringency in France. This event allows me to study the causal relation between environmental regulation with equity market response and firm valuation. Findings indicate that stock prices of firms operating in energy intensive sectors exhibited excess positive returns in response to the carbon tax rate suspension. In contrast, firms in less energy intensive sectors had excess negative returns. Robustness checks verify the unexpected nature of the announcement and affirm that investor did not under or over-react to the announcement and excess returns were maintained in days following the event.

Chapter 2

HOW DOES THE INCREASED SHARE OF RENEWABLE ENERGY IMPACT ELECTRICITY MARKETS AND CLIMATE?: A NATURAL EXPERIMENT USING THE COVID-19 NEGATIVE DEMAND SHOCK

2.1 Introduction

Electricity and heat generation make up 25% of global greenhouse gas (GHG) emissions, and the expansion of renewable energy is an important tool in achieving net-zero targets in the energy sector and mitigating climate change (IPCC 2014). Ambitious climate pledges and GHG reduction goals adopted at the local and national levels, coupled with generous support mechanisms and decreases in the marginal costs of producing electricity from renewable sources, increased the installed capacity of wind energy from 7.5 gigawatts (GW) in 1997 to 733GW in 2020. In addition, the installed capacity in solar energy increased from 0.27GW in 1997 to 707GW in 2020. (IRENA 2021). Along with the wide array of policies adopted in developed countries to promote renewable energy, developing countries also support electricity generation from local renewable sources to ensure energy security, reduce imported energy, and benefit the environment. However, the intermittent nature of renewable energy sources, particularly wind and solar energy, creates challenges for grid operators. The variability of renewable energy, which is largely predictable from daily and seasonal patterns, and intermittency, which is mostly unpredictable due to short-term fluctuations, make wind and solar energy non-dispatchable (Baker et al. 2013), meaning electricity suppliers relying

on renewable sources cannot ramp generation up or down. Hence, grid operators are obliged to optimize production from other suppliers to minimize costs, avoid blackouts, and reduce transmission constraints.

To examine the implications of rapid increases in the share of intermittent, non-dispatchable renewable energy, one can use two alternative empirical strategies. One can either identify a context where the installed capacity of renewable energy expands rapidly or detect a situation where the share of renewable energy in the electricity grid expands in a short time. In this paper, I adopt the second approach by leveraging the unique opportunity created by the COVID-19 pandemic lockdowns in Turkey. The lockdowns implemented in many countries restricted individuals' mobility and reduced the overall demand for electricity and the electricity supply from dispatchable sources, particularly fossil fuel power plants (Graf et al. 2021). Yet, supply from intermittent sources like wind and solar energy was unaffected by the impact of lockdowns. This situation translated into a rapid and exogenous increase in the share of electricity generated from renewable, non-dispatchable sources. The exogenous negative demand shock and concomitant increase in the renewable energy share (RES) in aggregate electricity generation created an opportunity to analyze how electricity markets and suppliers react to a rapid expansion of renewables. This analysis might be applicable to the numerous countries that might experience such an expansion in the coming years under ambitious climate pledges.

In this project, I analyze two first-order effects of rapid renewable energy expansion in Turkey's electricity markets. First, I look at how a higher RES impacts the ability of intermittent renewables to curb generation from fossil fuel-burning thermal power plants. Theoretically, the negative demand shock shifts the aggregate demand curve inwards and shifts the marginal producer from natural gas to coal power plants. I show that as these shifts occur, a marginal increase in wind

energy reduces generation from natural gas at lower, and coal and lignite power plants at higher magnitudes when compared to the regular demand period. During the lockdown, when the RES in total electricity generation increased almost 100%, a 1 megawatt hour (MWh) increase in electricity generated from wind energy reduced coal and lignite production by a further 0.22MWh and 0.025MWh, respectively, compared to the regular demand period. However, the marginal decrease in natural gas generation was curbed by 0.2MWh. This can be interpreted as wind energy displaced a similar amount of fossil fuel generation during and before Covid-19 but the fossil fuels comprising this displacement has changed in favor of dirtier fuels, coal and lignite. Second, I examine how the exogenous shock impacted the merit-order effect of renewables. I show that as the RES in the grid increases, their ability to reduce spot prices slightly declines. I find that a 1% increase in wind energy reduced spot prices in the day-ahead market by 0.187% during the lockdown period and 0.193% in the regular demand period, with a statistically significant difference of %0.05.

Regarding the second-order effects, I examine how GHG emissions and damages from carbon emissions in the electricity generation sector change with the variation in RES in the aggregate electricity supply. I find that with the rapid increase in RES, a 1% increase in wind energy decreased GHG (CO_2 , CH_4 and N_2O) emissions from thermal power plants by 0.037% compared to regular demand periods. In terms of the damages from GHG emissions, an additional 1 MWh of wind energy reduced additional damages by an amount equivalent to \$7.14, \$1.29 and \$20.02 from CO_2 , CH_4 and N_2O emissions during negative demand shock period, compared to the regular demand period. I also conduct a series of robustness checks using the dates corresponding to the COVID-19 lockdowns in previous years as placebo treatment periods. Results indicate that the effects I find cannot be observed in the placebo period, showing that the treatment effect is an outcome of the expansion in RES during the COVID-19 lockdown.

The identification strategy and the empirical context I use have several advantages. First, the negative demand shock driven by the COVID-19 pandemic lockdowns was unexpected and abrupt, allowing me to clearly distinguish the regular and negative demand shock periods. Second, Turkey is a developing economy with a sizable installed capacity for renewable energy and a growing wind energy sector (TUREB 2020). Participants in the electricity market operate in a privatized, well-functioning market comparable to the more mature markets of the developed countries. Third, Turkey’s electricity demand is predominantly met with electricity generation within the Turkish grid. Cross-border trade comprises less than 1% of the total electricity supply. Unlike Turkey, European and US settings maintain grid balancing with electricity generated in other interconnects or countries, making it hard to isolate the impact of demand shocks within a single interconnect or grid.

Previous research on the impact of renewables on the electricity markets focuses on the merit-order effect, generation from thermal power plants, and emissions, as detailed in Section 2.2. However, those aiming to show a causal relationship focus on the exogeneity of variations in the share of wind or solar energy as the basis of their inference. This paper contributes to the literature by employing an identification strategy that rests on a natural experiment induced by the COVID-19 lockdowns, which can be considered analogous to a rapid expansion of renewable sources and RES in the electricity grid. The findings in this paper thus allow policymakers and grid operators to understand how the future of expanding intermittent renewables could impact the operation of the electricity grid while reaching a net-zero carbon target and attaining other climate goals.

The paper is organized as follows: Section 2.2 provides an overview of the literature on the effects of intermittent renewable energy on electricity market outcomes and how COVID-19 lockdowns impacted electricity generation and consumption. Section 2.3 gives background information on

how electricity markets operate and intermittent renewables are integrated into electricity systems. Sections 2.4 and 2.5 introduce the empirical methods and data used to answer the research questions for this project, and Section 2.6 presents the findings. The paper concludes with a discussion about policy implications and suggestions on future research in Section 2.7.

2.2 Existing literature

In the last two decades, the expansion of renewable energy, especially intermittent and highly variable wind and solar energy, has attracted significant scholarly interest. In particular, researchers have studied the effect of renewable energy on zero-emission and low marginal cost sources in the context of electricity markets and climate change mitigation. As policymakers aim to decarbonize the electricity grid to achieve net-zero targets and other climate mitigation pledges, it is crucial to understand how the electricity grid and dispatchable conventional generation capacity respond to the expansion of renewable energy.

Two main strands of the economics literature focus on the impact of renewable energy on electricity market outcomes, such as wholesale or spot prices, thermal power plant output, and emissions of GHG and other pollutants. The first strand relies on simulations that examine the long-run effects of renewable energy expansion (Fell and Linn 2013, Gowrisankaran et al. 2016). Simulation models in these analyses must rely on simplifying assumptions, which do not fully reflect the dynamics of the electricity market.

The second strand relies on microeconomic tools to examine fine-grained, high-frequency electricity market data. The richness of grid data from mature markets allows empirical estimations to identify the impact of renewable energy (Kaffine et al. 2020). These studies usually use the exogenous variation in renewable energy, particularly wind, as the predictor of the variation in

main electricity market outcomes (Cullen 2013, Fell and Kaffine 2018, Kaffine et al. 2013, Novan 2015). Some of these empirical studies analyze the impact of wind on specific electricity market outcomes in different regions. A group of them focuses on the wholesale or spot-price (merit-order), reducing effects of renewable electricity in different countries. In Australia, (Forrest and MacGill 2013) find a marked negative impact of renewable energy on spot market prices. In the US, Woo et al. (2011), Woo et al. (2013) and Woo et al. (2016) estimate the effect of different renewable energy sources in Texas, the Pacific Northwest, and California, respectively, and find that wind and solar energy have substantial electricity price-reducing effects. In Germany, Sensfuß et al. (2008) show that the merit-order effect is significant enough to offset costs incurred on consumers through feed-in tariffs. This finding is corroborated by Würzburg et al. (2013) and Ketterer (2014). In Spain, Gelabert et al. (2011) identifies a 4% decrease in the wholesale prices, with a marginal increase in wind energy. Similarly, Acar et al. (2019) find that wind and run-of-river hydro reduced spot prices in the day-ahead markets in the 2012–2017 period in Turkey. In Italy, Clò et al. (2015) show that solar and wind energy reduce wholesale and spot prices. However, they also find that as the installed capacity and generation from renewable sources increases, the impact of renewable energy on prices declines, which is in line with the findings of this paper related to the merit-order effect.

Yet, some other studies point out the uncertainty in the price reducing effects. For example, Ketterer (2014) emphasize the increasing volatility in wholesale prices. In Ireland, O’Flaherty et al. (2014) find a negligible impact of the increases in wind energy share on wholesale prices, and Swinand and O’Mahoney (2015) show that the marginal electricity price drops by a mere 0.06%, with a 1% increase in electricity generated from wind energy.

In terms of reductions in emissions from fossil fuel power plants, research has been clustered

in the US due to high frequency and plant-level continuous emissions monitoring systems (CEMS) data. It is widely accepted that the electricity generated from renewable energy displaces some of the GHG and other pollutant (SO₂, NO_x, PM2.5 or PM10) emissions from conventional thermal power plants. However, renewables offset varying emission levels in different regions depending on the size and composition of the local thermal generation capacity. [Graff Zivin et al. \(2014\)](#)'s analysis shows that marginal emissions rates vary by location and time of the day in the US, implying that the quantity of emissions displaced by renewable energy also changes at the regional level. A similar finding by [Callaway et al. \(2018\)](#) adds that emissions displacement on a per MWh basis does not vary across wind, solar, or energy efficiency policies. Yet, an analysis by [Novan \(2015\)](#) focusing on the ERCOT region in Texas shows that different types of renewable energy sources (i.e., wind and solar) provide different levels of marginal benefits in terms of price reductions and societal damage abatement.

Apart from the studies looking at the short-term effects of increasing renewable production on the electricity market outcomes, [Bushnell and Novan \(2021\)](#) examine the medium-run implications of renewable energy capacity expansion for operating margins of thermal power plants and wholesale electricity prices. They show that a higher penetration of solar energy in California increases generation and operating profits in natural gas power plants that are more flexible to operate but less fuel-efficient and dirtier. At the same time, the higher penetration decreases the profits of low marginal cost conventional generators. As a step further in the applied microeconomic methods in this strand of the literature, [Andersen et al. \(2019\)](#) conducted a field experiment and used electricity grid data to causally identify the effects of high wind and solar energy penetration. They show that shifting residential consumption from high to low demand periods of the day can reduce the costs related to integrating GHG-free wind and solar electricity production into the grid.

The analysis in this paper is an extension of the second strand of the literature. The main contribution of this analysis is the use of an exogenous shock to emulate a rapid expansion of the share of renewable energy in the grid rather than a sole focus on the short-run and contemporaneous effects of variation in the renewable energy output. While the outcome variables and findings of this analysis are in line with the previous empirical analyses in the literature, the identification strategy allows me to examine a condition that grid operators could face in the long run with the expansion of renewable energy and RES in electricity markets.

Even though this analysis does not focus specifically on the impact of the COVID-19 lockdowns on electricity market outcomes, it contributes to the scholarly work that provides empirical evidence of the effects of these lockdowns. The most straightforward outcomes of these lockdowns are reductions in aggregate demand and changes to daily and weekly demand profiles. Scholars document a general decline in demand for electricity, composed of a reduction in commercial and industrial demand in the cases of the US (Cicala 2020), Brazil (Carvalho et al. 2017), Spain (Santiago et al. 2021), India (Beyer et al. 2021), and the UK (Krarti and Aldubyan 2021). Also, as electricity demand and output decline, COVID-19 lockdowns reduce emissions of GHGs and other pollutants, as shown in the cases of Ontario (Abu-Rayash and Dincer 2020), East China (Filonchyk et al. 2020), and Baghdad (Hashim et al. 2021). In terms of merit-order effects, Ghiani et al. (2020) show that wholesale prices and spot prices in the day-ahead electricity market decrease during lockdowns in Italy. In Graf et al. (2021)'s recent analysis, the authors find that COVID-19-related restrictions reduce day-ahead market prices but increase re-dispatch costs due to distribution bottlenecks stemming from the intermittent renewable share in the grid.

2.3 Background information

2.3.1 How electricity markets and electricity dispatch process work?

Electricity markets have three major segments from the power plants to the end-users: generation, transmission, and distribution. The generation segment is undertaken by power plants. But these power plants are usually located geographically far from the end users in households, commercial buildings or industrial sites. The second segment, transmission is used to transport electricity in long distances. To reduce the loss on transmission lines electricity is stepped up via a transformer to high voltages during this stage. Following the transmission segment, in the distribution segment high voltage electricity is stepped down which makes it accessible to end consumers and then distributed to industrial, commercial and residential consumers at different voltages. Before the deregulation and reorganization of utilities in the 80s and 90s, in the developed and developing world, these three segments were vertically integrated and usually owned by a single company (like in the US) or a public utility (like in Europe). Following the waves of deregulation in the 80s and 90s, electric utilities usually started to manage the distribution grid only, and the vertically integrated structure was broken into separate and independent generation, transmission, and distribution entities. However, deregulation not only broke down and privatized the vertically integrated structure of utilities; it also created new regulatory institutions for the maintenance of a competitive and reliable grid. These institutions and regulations are markedly different from those in other deregulated commodity or service markets (Griffin and Puller 2009), mainly as a result of the special physical characteristics of electricity as a commodity and the attributes of the electricity market.

Given that electricity cannot be stored efficiently, electricity demand should match the electricity

supply at all times. Otherwise, blackouts can occur with a slight mismatch of supply and demand. To overcome this problem, the system operator needs to solve a complex cost minimization problem in real-time, subject to constraints in unit-generation capacities and transmission limits. Electricity demand is highly variable and quite inelastic, so the perpetual clearing of the market depends on the management of the electricity supply. The system operator arranges the electricity supply bids from the lowest to the highest to form the electricity supply curve, known as the merit-order or dispatch curve. Power plants with the lowest variable operating costs usually dispatch (or produce) first, and plants with higher variable operating costs are dispatched consecutively at higher demand levels. ¹

We can divide the costs of running a power plant into two: fixed and variable. The former largely consists of capital costs and is not directly related to how much electricity is produced. The latter is the sum of operating expenses and fuel costs and is usually positively correlated with the amount of electricity produced in a power plant. Renewable energy power plants have zero fuel costs and lower operation and maintenance expenses compared to fossil fuel power plants. Besides, wind and solar power plants do not incur the opportunity costs of depleting the natural reserves like hydropower does. Hence, their short-run marginal costs are essentially zero. Where there is a price on the carbon emitted from stationary combustion for energy generation, operating costs of fossil fuel power plants are raised even higher. ²

Power plants providing baseload electricity to the grid usually work almost all hours of the day

¹While grid operators usually rely on the merit-order for dispatching power plants, they might dispatch out of merit order under certain circumstances. When there are network constraints or interruptions, unexpected facility outages that hinder predetermined dispatch instructions or non-scheduled generation changes, grid operators might need to dispatch out of merit order and notify market participants in short notice (hourly or 30 minutes intervals) for intra-day trading to balance the grid.

²Variable costs incurred due to carbon pricing are a function of the carbon intensity of the fuel used and the heat rate of the power plant.

and every day of the year. These have low variable operating costs at a constant production rate but higher costs during ramping up or down or start-up and shut-down processes. Coal, lignite, and nuclear power plants usually provide the baseload demand, working almost at full capacity.

³ Coal and lignite power plants tend to have a lower marginal cost than other fossil fuel power plants, especially in developing countries. In recent years, though, natural gas power plants have moved ahead of the coal power plants in the supply queue in North America (Cullen and Mansur 2017) due to the drop of natural gas prices driven by the shale boom (Hausman and Kellogg 2015). However, developing countries with high coal reserves and imported natural gas did not experience a similar reshuffling of the merit order sequence.

Peaker power plants are located at the higher levels of the merit order curve due to their high operating costs and generate electricity during the highest-demand periods. Between peaker and baseload power plants are the cycling units that adjust their output according to daily fluctuations in demand. Natural gas power plants are usually these cycling units, operating as the marginal producers. Their marginal cost generally sets the price for electricity prices both in wholesale and in spot markets (day-ahead and intra-day) (Linn and Muehlenbachs 2014).

While fossil fuel power plants (coal, lignite and natural gas) are dispatchable ⁴, renewable energy sources relying on natural occurrences (like blowing wind and shining sun) have high variability and are intermittent. They can enter the grid only when their output is available. The system operator almost always allows intermittent renewables when available due to their very low variable cost and cost-minimization goal of the grid operator. ⁵ As intermittent renewable energy generation

³For more details, see <https://www.eia.gov/todayinenergy/detail.php?id=7590>

⁴While nuclear power plants are theoretically dispatchable (Joskow 2011), due to constraints imposed by the fission process it is not possible to ramp generation up and down as quickly as fossil fuel power plants. Consequently nuclear power plants provide the baseload for steady electricity generation.

⁵Except for the times of wind energy curtailment when demand needs to be balanced to avoid transmission congestion in high demand volatility.

increases, it is added to the lower end of the merit order curve and shifts the supply curve outwards. This leads to a decrease in electricity prices and generation from dispatchable sources, as short-run electricity demand is perfectly inelastic. This process is visually represented in Figures 2.1a and 2.1b. In the case with no wind energy shown in Figure 2.1a, the baseload is provided by lignite and coal power plants, and natural gas power plants are cycling and peaker plants. With the addition of wind energy in Figure 2.1b, the supply curve shifts outward, electricity generation from natural gas declines, and the price of electricity drops from P_1 to P_2 .

2.3.2 Electricity markets and wind energy in Turkey

As in other parts of the world, electricity markets in Turkey were vertically integrated and publicly operated under TEI (Turkish Electricity Institution) ⁶ until the 90s. The deregulation process started in 2001 and the generation, transmission, and distribution roles of public utilities were separated in 2001 with the Electricity Market Law. ⁷, ⁸ This legislation also paved the way for the privatization of electric utilities regulating distribution. With this privatization, Turkey's grid was divided into 21 electricity distribution regions interconnected in a single grid. In 2004, the electricity market balancing and settlement regulation brought bilateral agreements and pricing mechanisms into the Turkish electricity market. Day-ahead and balancing markets started operating in 2011, and EXIST (Energy Exchange in Istanbul) ⁹ started operating in March 2013 with the new

⁶Türkiye Elektrik Kurumu (TEK) in Turkish

⁷Turkish Electricity Generation Corporation (Türkiye Elektrik Üretim A.Ş. (TEAŞ)) was divided into three separate and independent corporations for electricity generation, transmission and distribution, namely Electricity Generation Corporation (Elektrik Üretim A.Ş. (EÜAŞ)), Turkish Electricity Transmission Corporation (Türkiye Elektrik İletim A.Ş. (TEİAŞ)) and Turkish Electricity Trade and Contracting Corporation (Türkiye Elektrik Ticaret ve Taahüt A.Ş. (TETAŞ)).

⁸See [Law No. 4628 - Electricity Market Law](#) for details.

⁹Elektrik Piyasaları İşletme A.Ş. (EPIAŞ) in Turkish

Electricity Market Law.¹⁰

In the last decade, the Turkish government focused on generating electricity from local energy sources and started to provide generous subsidies in the form of feed-in tariffs for electricity generated from renewable energy sources.¹¹ Turkey's renewable energy support mechanism attracted new investments in the renewable energy sector and resulted in an increase in the share of wind energy in Turkey's energy mix from 1% in 2010 to almost 10% in 2021, as seen in Figure 2.2, indicating a ten-fold increase in less than a decade (Acar et al. 2019). This rapid increase and the intermittent aspect of wind and solar energy required the system operator to initiate the operation of the intra-day market at the end of 2015 for market participants to revise their bids in the day-ahead market in case of supply imbalances (Selcuk et al. 2022).

The market structure for electricity generation is highly segmented for renewable energy, and the top four firms comprise less than 25% of the total electricity generated and installed capacity. Figure 2.3 shows the distribution of the shares of the top 20 companies in the total installed wind energy capacity in Turkey. If we take the shares of all firms, we find that the Herfindahl-Hirschman index of the wind energy generation industry is 266.2 which can be considered as an industry with low market concentration with regard to the Horizontal Merger Guidelines of the US Department of Justice and Federal Trade Commission (2010). Private companies with investments in renewable energy do not have a substantial presence in dispatchable energy generation from fossil fuels either. This scattered market structure in Turkey's electricity markets prevents possible price gouging or other market-distorting practices in the wind and solar energy sector.¹²

¹⁰See Law No. 6446 - Electricity Market Law for details.

¹¹Currently the state feed-in tariffs for renewables stand at \$0.7/MWh.

¹²It must be noted that Acemoglu et al. (2017) show that when renewable energy operators also own thermal energy power plants, there might be welfare-reducing consequences. By reducing their thermal power generation, these producers offset price decreases due to zero marginal cost renewable energy. In Turkey, the state-owned electricity generation company (EÜAŞ) has a significant share in the installed capacity of coal and hydropower plants. This

2.4 Empirical Methods

The identification strategy of this analysis rests on the exogeneity of the negative demand shock during COVID-19 lockdowns and wind energy as the treatment. The negative demand shock was abrupt and unexpected. Policymakers or market operators could not respond to it by increasing installed capacity or higher cross-border electricity trade. These factors make the negative demand shock plausibly exogenous. Also, we can assume that wind energy is exogenous in the short-run. Controlling for potentially endogenous hourly and daily variations in wind power due to seasonality or daily patterns of wind speeds, electricity generated from wind energy should predict changes in electricity generated from fossil fuel-power plants as well as day-ahead market prices without confoundedness. The exogenous variation in the aggregate demand and share of wind energy provides a unique natural experiment setting where the share of renewable energy expands rapidly due to the sharp decrease in demand.

To measure the magnitude of changes in electricity market prices, generation in fossil fuel power plants, and GHG emissions due to wind energy share expansion, I use the COVID-19 lockdown period in Turkey, March 15-May 31, 2020, as the treatment period. Turkey reported its first COVID case on March 10, 2020, and the first measures to restrain the mobility of the public were adopted on March 16, 2020, with the closure of schools (Cakir 2020). Restrictions expanded on March 27, 2020, and on April 11-12 total lockdowns in 31 metropolitan municipalities were implemented. Because cases started to plummet during May 2020, most restrictions were lifted as of May 31, 2020. Hence, it is reasonable to take March 15-May 31, 2020, as the negative demand shock period.

might give EÜAŞ an opportunity to influence prices in Turkey (Sirin and Yilmaz 2020). Future research might look into the potential market-distorting effects of these companies with diversified portfolios in the electricity generation sector.

The period preceding COVID-19 lockdowns serves as the control period.¹³ The change in total daily production in MWh’s across 2019 and 2020 can be seen in Figure 2.4. The slump in daily electricity generation is visibly clear after March 15, 2020, the beginning of the treatment period. The magnitude of the decrease in production can be seen in Figure 2.5. Compared to the baseline of the average weekly generation in 2017-2019 period, after the 10th week of the year which corresponds to mid-March, electricity generation declined by 20% and almost reached 25% by mid-April. Bahmanyar et al. (2020)’s analysis shows that Turkey’s electricity demand reduction of approximately 20-25% during COVID-19 lockdowns was quite similar to that of European countries with stricter lockdown measures.

To examine how hourly electricity generation from wind impacts electricity generation from power plants using fossil fuels, lignite, coal, and natural gas on average, I use the model below¹⁴ :

$$F_h = \beta W_h \times Covid + \theta[f(D_h) \times Covid] + \alpha_{h,m,y,w} + \delta_d + \epsilon_h \quad (2.1)$$

where F_h is the aggregate hourly electricity generation in MWh from lignite, coal, and natural gas power plants separately at hour h . W_h is the aggregate hourly generation in MWh from wind power plants, $Covid$ is a binary variable equal to 1 if the observation is within the COVID-19 lockdown period (March 15 - May 31, 2020), and 0 otherwise (January 1, 2016 - March 15, 2020). The coefficient of interest is β , which estimates the percent change in fossil fuel-power generation during the negative demand shock due to a 1% change in wind energy, compared to the regular demand period. D_h is the aggregate consumption or demand at hour h . I include higher-order

¹³The details of the COVID-19 lockdown related measures during March-June 2020 in Turkey are listed in appendix section A.3.

¹⁴This model follows Novan’s (2015) analysis for valuing wind energy’s benefits in ERCOT’s Texas Interconnect in the US.

polynomials of demand to account for differences in demand profiles across the different periods of the panel, which is denoted by the function $f()$. I also interact these different functional forms of demand with the *Covid* binary variable to take into account the demand profile changes during and before lockdowns. ¹⁵ $\alpha_{h,m,y,w}$ is an hour (h) of day fixed effect that varies by month (m) of the year, year (y), and day of the week (w). I construct this fixed effect variable by generating a unique value for each hour of the day in each month of the year, each year, and each day of the week, which adds 8904 binary variables to the model. ¹⁶ δ_d is the daily fixed effects for each day d in the whole sample from January 1, 2016 to May 31, 2020, which adds 1612 binary variables to the model. ¹⁷ I also use Newey-West standard errors with a 24h lag to account for serial autocorrelation.

To analyze if a demand shock with a higher magnitude, proxying for a higher share of wind energy penetration alters the impact of wind energy on electricity generated by fossil fuel power plants, I divide the COVID-19 treatment period into two. The first period, designated as “Early COVID,” covers the dates from March 15, 2020, to April 20, 2020. The second period, designated as “Late COVID,” covers the dates from April 20, 2020, to May 31, 2020, which is when the tougher COVID-19 restrictions caused industrial and commercial electricity use to plummet even more than the “Early COVID” period. To estimate the impact of demand shocks with different magnitudes during early and late COVID periods separately, I use a modified version of Equation 2.1 below:

¹⁵As an illustration, when I include higher-order polynomials up to the third factor, this term becomes $\sum_{i=1}^3 \theta_i [Ln(D_t^i) \times Covid]$.

¹⁶To create this fixed effect variable, I create a unique value for each of the 24 hours of the day for 12 months of the year between 2016 and 2019, 7 days of the week and 4 years between 2016 and 2019, which generates 8064 unique values. Then for the first 5 months of 2020, I create a unique value for 24 hours of the day for 5 months of 2020, 7 days of the week, which generates 840 unique values. Together, these two sets add up to 8904 unique values for this fixed effects variable.

¹⁷To generate this variable, I created a unique value for each day in the sample between January 1, 2016 to May 31, 2021. Number of days in 2016 was 366, each year between 2017-2019 had 365 days, and the first five months of 2020 had 151, which add up to 1612.

$$F_h = \sum_{j=1}^2 \beta_j W_h \times Covid_j + \sum_{j=1}^2 \theta_j [f(D_h) \times Covid_j] + \alpha_{h,m,y,w} + \delta_d + \epsilon_h \quad (2.2)$$

where $Covid_j$ indicates two binary variables. For “Early COVID,” it is equal to 1 when $j = 1$, for “Late COVID,” it is equal to 1 when $j = 2$, and both of them equal to 0 otherwise. Again, the coefficient of interest is β , which estimates the percent change in fossil fuel power generation due to a percent change in wind energy in the early (β_1) or late (β_2) COVID-19 period in comparison to the pre-COVID period.

To estimate the merit-order effect of wind energy on real-time electricity prices, I use a model similar to the one in Equation 2.1 but all variables are in natural logs, in order to estimate the elasticity of electricity prices to contemporaneous variations in wind energy:

$$Ln(P_h) = \beta Ln(W_h) \times Covid + \theta [f(Ln(D_h)) \times Covid] + \alpha_{h,m,y,w} + \delta_d + \epsilon_h \quad (2.3)$$

where $Ln(P_h)$ is the natural log of the hourly spot price of electricity in the day-ahead market in US Dollars (USD) or Turkish Liras (TRY) per MWh in real terms. $Ln(W_h)$ and $Ln(D_h)$ are the natural logs of the hourly wind energy and aggregate demand from Equation 2.1.

As Cullen (2013) points out, thermal generators burning different fuels and using different combustion technologies have varying emission rates. Hence, I would expect the GHG emission abatement effect of wind energy to differ significantly during the rapid expansion period, as power plants reduce their output with the expansion of RES. I estimate the impact on GHG emissions and damages from fossil-fuel power plants using the same type of a regression model in Equation 2.1. I replace the outcome variable with hourly emissions of each GHG, CO₂, N₂O, CH₄, and quantify

damages related to these emissions.¹⁸

To test the robustness of the findings, I also run placebo tests by introducing a placebo treatment period of March 15 to May 31, 2019, which is the corresponding time frame to the negative shock period during COVID-19 lockdowns. The placebo control period is from January 1, 2016 to March 14, 2019. I expect that, in the absence of the negative demand shock and the increase in RES, the impact of wind energy on outcome variables in the models above should not be significantly different during the placebo treatment period when compared to the placebo control period controlling for the hourly, daily and seasonal variation in wind energy. Results of the placebo tests will be discussed along with the main results in Section 2.6.

2.5 Data

For the analysis described in Section 2.4, I use a unique dataset that I assembled with data publicly available to researchers from the Turkish Energy Exchange in Istanbul (EXIST), Ministry of Environment, Urbanization, and Climate (MoEUC), Energy Market Regulatory Authority (EMRA), US Department of Energy’s Energy Information Administration (EIA), US Environmental Protection Agency (EPA), and the European Union (EU).

I collected the data on hourly day-ahead and intra-day market prices, hourly electricity generation at the plant level aggregated by fuel type, and hourly consumption (aggregate demand) from the EXIST database.¹⁹ The EXIST data covers the period from January 1, 2016, the first day in the publicly available records, to May 31, 2020, the end date of the first lockdowns in Turkey.

¹⁸Six main GHG from the Kyoto protocol include three fluorinated gases (f-gases) as well, HFCs, PFCs and SF6 (UNFCCC 2008). Yet, most of the F-gases emissions come from electronics manufacturing, use of electrical equipment (including electricity transmission and distribution) and magnesium and aluminum production (EPA 2015). Electricity generation produces negligible amounts of F-gases, hence these gases are not included in this analysis.

¹⁹See EXIST website for details: <https://seffaflik.epias.com.tr/transparency/>

²⁰ This spans a total of 1,614 days and 38,734 hours.

Turkey does not have an emissions monitoring system at the plant level similar to the EPA’s CEMS in the US, and emissions data collected by the MoEUC from fossil fuel burning power plants are not publicly available even at the annual level. ²¹ To circumvent this data limitation, I predict the hourly emissions at the plant level data using the formula below:

$$E_{ph} = Prod_{pt} \times HR_p \times Conversionfactor \times Emissionfactor_p \quad (2.4)$$

where E_{ph} is the estimated GHG emissions (CO₂, CH₄, N₂O) in plant p at hour h in metric tons. $Prod$ is the hourly production in MW in plant p at hour t , collected from the EXIST database. HR is the heat rate in BTU per MWh at plant p . I use the EPA (2009) report on new coal power plant performance cost estimates to generate heat rates for 57 coal power plants in operation in Turkey. The report distinguishes the heat rate of coal power plants, using bituminous coal and lignite by fuel type and with subcritical, supercritical, and ultra-supercritical steam cycle types. The coal power plant sizes covered in this report range from 400MW to 900MW. I apply the standard heat rates for each fuel, steam cycle, and installed capacity from the report to the closest corresponding coal and lignite power plant in Turkey. I use the EIA (2021) Electric Power Annual Report 2020 to generate the heat rates for 279 natural gas power plants in operation in Turkey. ²² The report identifies gas turbine and combined-cycle natural gas power plants, and I apply the average heat rates for these two types for the years 2015-2020 to the corresponding type of natural gas power plants in Turkey.

²⁰See Appendix A.3 for the timeline of Turkey’s containment measures during the first wave of the COVID-19 pandemic.

²¹European Union (EU) funded projects supporting the alignment of Turkish legislation with EU emission regulations provide emission factors for different types of power plants in Turkey with detailed information about plant characteristics. Another option could be using this partial dataset for some thermal power plants, but a comparison of this data with the data I generated did not yield a meaningful difference.

²²See Table 8.2 of the EIA report for details of this data.

For the *Conversionfactor*, I use the constant converting TJ to BTUs (equal to 94,7817,077.75). *Emissionfactor* is the emissions generated by the fuel (coal, lignite, or natural gas) used at plant p to generate a 1 TJ of energy. I use the emission factors of fuels used for stationary combustion in energy industries from the [IPCC \(2006\)](#) Guidelines for National GHG Inventories. ²³ It must be noted that, overall, this method of estimating hourly GHG emissions at the plant level might not fully reflect the actual values, as it focuses on emissions from net generation released to the grid, which does not cover the electricity the plant uses to run necessary equipment. CEMS data, for instance, does not provide emissions for net generation but provides emissions at power plant stacks. Yet, despite the lack of plant level total emissions, the net generation emissions should serve as a good approximation and a second-best solution given the data limitations for the analysis in this paper.

To measure the impact of renewable energy expansion on the abatement of societal damages from carbon emissions, I replace the outcome variable in equation 2.1 with the monetary value of damages. To generate the damages incurred from GHG emissions, I use Interagency Working Group's (IWG) most recent social cost of carbon (SCC) estimation for 2020 GHG emissions (2021), for CO₂ which is equal to a mean value of \$51/tCO₂, for CH₄ which is equal to a mean value of \$1,500/tCH₄ and for N₂O which is equal to a mean value of \$18,000/N₂O, all with a 3% discount rate. It should be noted that the integrated assessment models (IAMs) that IWG uses to estimate the SCC, namely DICE, FUND and PAGE models, omits some damages from GHG emissions. To name a few, these models do not take into account damages due to local pollutants such as NO_x, SO₂, CO, PM 2.5 or PM 10, impacts on labor productivity, ocean acidification or biodiversity loss (Howard 2014). So, while IWG report provides a clear guideline to quantify damages from GHG

²³See [Table 2.2](#) of the report for details of this data.

emissions, the SCC estimates in the report and analysis using these estimates should be regarded with caution.

For estimating the combined impact of the negative demand shock and the exogenous wind power on spot-market prices, I use real prices in both Turkish liras and US dollars. I gathered the nominal electricity market clearing price data in TRY and USD from the EXIST database.²⁴ To calculate the real prices in TRY, I use month-over-month consumer price inflation data from Central Bank of the Republic of Turkey (CBRT).²⁵ To calculate the real prices in USD, I use the consumer price index for all urban consumers from Federal Reserve Economic Data (FRED).²⁶

The summary statistics of the whole panel are presented in Table 2.1. The average values by different fuels and methods show that between 2016 and 2020, approximately 32% of total electricity generation come from wind and hydropower, whereas fossil fuel power plants (coal, lignite, and natural gas) make up almost 65% of total generation. Among fossil fuel power plants, natural gas has a 30% share, and coal and lignite a 35% share, indicating a high reliance on fossil fuels despite a relatively large renewable capacity. The standard deviation figures show a high variation in renewable sources compared to fossil fuel-powered electricity generation.

I also present summary statistics for different segments of the panel in Table 2.2. I present four alternative panels: i) the COVID lockdown period from March 15, 2020, to May 31, 2020 (column (1)); ii) the pre-COVID period between January 1, 2016, and March 14, 2020 (column (2)); iii) the period corresponding to COVID-19 lockdown dates for 2019, March 15, 2019–May 31, 2019 (column (3)); iv) the period corresponding to pre-COVID-19 lockdown dates for 2019, December

²⁴EXIST reports hourly market clearing prices in the day-ahead markets in Turkish liras, US Dollars and Euros. For details, see: <https://seffaflik.epias.com.tr/transparency/piyasalar/gop/ptf.xhtml>

²⁵See [CBRT Consumer Prices](#) for the data.

²⁶See [FRED CPI](#) for the details of data.

15, 2019-March 14, 2019 (column (4)). First, as expected, we see that generation slumped at a high magnitude during COVID-19 lockdowns. The discrepancy between the aggregate daily consumptions in 2019 and 2020 can also be seen in Figure 2.4. In Figure 2.5, we see that while electricity generation in 2020 was slightly higher than the average production between 2017 and 2019, following the week of COVID-19 lockdowns, production decreased almost by 20%. By the end of the lockdowns, it had reached 25%, a significant percentage given that Turkey did not impose the extreme measures that we saw in Italy or the UK during the early days of the pandemic. The distribution of electricity generation also changed during the COVID-19 lockdowns, as seen in Figures 2.6 and 2.7. Second, in line with the expectations of stylized facts, real day-ahead market prices decreased by 10% in TRY and 15% in USD, compared to March 15 through May 31, 2019. The price slump can be examined in Figure 2.8. While prices in USD were quite similar between the 2020 and 2017-2019 averages before the lockdowns started, in the first weeks of COVID-19 measures, prices diverged from the historical averages and declined from \$40/MWh to almost \$20/MWh.

In terms of the daily distribution of consumption, Figure 2.9 shows how consumption patterns in week times changed between lockdowns and the preceding period. During the pre-COVID period, weekdays (following the Sunday denoted in grey in the plot) were similar to one another yet quite distinct from weekends. However, during the lockdown period, almost all days were similar to each other in terms of the distribution of consumption by each hour of the day. This is probably related to the massive decreases in commercial and industrial electricity consumption, only partially replaced by residential consumption.

In terms of production by fuel type, natural gas had the largest decrease as natural gas power plants are usually located between baseload and peaker power plants in the merit-order curve and are usually the marginal producers in Turkey's electricity markets. The negative demand shock

might have shifted the marginal producer from natural gas to other fossil fuel power plants like coal and lignite, depending on the hour of the day. Figure 2.1c illustrates this potential change: when the COVID-19 lockdowns shift the demand curve inwards, the marginal producer changes from natural gas to coal power plants.

Figures 2.10 and 2.11 shows that the average hourly absolute production and share of total production patterns of coal and natural gas power plants during COVID-19 lockdowns changed dramatically compared to the pre-COVID period. Lignite power plants, which are costly to turn on and ramp-up, had similar production patterns across two periods and continued to serve as baseload. Renewable energy production patterns did not change as production in these plants generally relies on exogenous factors of wind and water availability. Finally, due to the decrease in coal and lignite production, overall GHG emissions decreased during COVID-19 lockdowns compared to previous periods in alternative panels.

2.6 Findings

2.6.1 Generation from fossil fuel power plants

Table 2.3 depicts the combined impact of wind energy and the negative demand shock on electricity generation from fossil fuel power plants. The results are organized for each type of fossil fuel used in electricity generation, natural gas, lignite, and coal, in different columns. Prior to the negative demand shock, contemporaneous wind power reduced natural gas the most, compared to coal and lignite. As seen in Column (1) Row (1), a 1MWh increase in wind power decreased electricity generated from natural gas by 0.52MWh, on average in the absence of the COVID-19 lockdowns and the ensuing negative demand shock. This is not surprising as natural gas power plants usually

serve as the marginal producers during regular demand times due to their ability to start up fast and ramp up or down with high flexibility. Also, as a result of the weak environmental regulations, lack of carbon pricing and the import cost of natural gas, using natural gas for electricity generation is costlier than coal and lignite. Therefore, natural gas power plants are located at the higher end of the merit-order curve. However, with the onset of the negative demand shock, the sign of our coefficient of interest, β turns out to be positive, meaning that a lower demand attenuates wind energy's ability to curb electricity generation from natural gas. A 1MWh of wind energy reduces electricity generation from natural gas by approximately 0.32 MW during COVID-19 lockdowns and by 0.53MW during the regular demand period. This signifies a 0.21MWh (the coefficient estimate of β) decrease, on average, for a 1MW of wind energy's ability to reduce electricity from natural gas during and before the negative demand shock.

Lignite is the cheapest fuel to produce electricity in Turkey, and on average, lignite power plants have lower marginal costs than other fossil fuels. Hence, lignite power plants serve as the baseload in the grid, following renewable energy sources in the merit-order curve, due to the zero or low-marginal cost of the latter. Their production does not fluctuate during different hours of the day. Therefore, as Figure 2.10(d) also illustrates, lignite production is relatively flat throughout the day, both during and after the negative demand shock. As lignite power plants rarely ramp up or down, intermittent wind energy does not cause fluctuations in electricity generation from lignite during the negative demand shock. As seen in Column (2) of Table 2.3, a 1MWh higher electricity generation from wind energy reduces electricity generation from lignite power plants by 0.013MWh in regular demand periods, a significantly lower amount than the impact on natural gas power plants. During the COVID-19 period, the expansion of wind energy had a modestly stronger impact on electricity generation from lignite: 1MWh of additional wind energy during this period

decreased electricity from lignite power plants by 0.025MWh compared to regular demand periods.

Compared to lignite power plants, coal power plants are equipped with newer advanced turbines and more efficient combustion technology (i.e., super-critical), and thus, are less costly to ramp up. As Figure 2.10e demonstrates, the average hourly production profile of coal power plants resembles that of natural gas power plants (Figure 2.10f) during the regular demand period. Yet coal (imported, anthracite or asphaltite²⁷), as a fuel input, is more costly than lignite due to lignite extraction in Turkey. Consequently, coal power plants are generally positioned between lignite and natural gas power plants in Turkey's merit-order curve. During the negative demand shock period, it is theoretically expected that the marginal producer shifts from natural gas power plants to coal power plants, and the increased share of wind energy reduced production from coal power plants at a higher magnitude compared to regular demand periods. As reported in Table 2.3 Column (3), we see that during the pre-COVID period, a 1MWh of wind energy reduced electricity generation from coal power plants by 0.12 MWh. Combined with the negative demand shock, 1 MWh of wind energy reduced a further 0.21MWh of electricity from coal.

Results related to the impact of wind energy on fossil fuel power generation suggest that a rapid expansion in RES accelerates the reduction in coal and lignite production, as the installed capacity of thermal power plants cannot change in the short run. To examine the differential impact of a more profound negative demand shock, I also compare the effect of wind energy on fossil fuel power generation during early (March 15-April 20, 2020) and late (April 21-May 31, 2020) COVID lockdown periods. As Figure 2.12 demonstrates, not much difference exists between the amount of natural gas used in the two periods. For lignite, there is a slight decrease in the late COVID

²⁷Anthracite and asphaltite coal are usually used in metallurgical industries such as steel production due to their high calorific value. Electricity generation from anthracite and asphaltite is approximately 1.5% and 1% of the aggregate electricity generation in Turkey respectively. The rest of the electricity generation from coal comes from imported coal.

period, while for coal, the impact of wind energy is much larger. During the late COVID period, 1MWh of wind energy displaced more than 0.5 MWh of electricity generated from coal, whereas during the early COVID period, this number remained below 0.3MWh.

A threat to the identification strategy of this analysis would be a similar effect to occur in previous years, as that would suggest that the effect is not about the negative demand shock. Therefore, I examine whether the impact of wind energy was the same in placebo treatment periods. Table 2.4 shows the results of the placebo test where I used March 15-May 31, 2019, as the treatment period and the period preceding it as the control period. Estimates show that the magnitude of the effect of wind energy on generation from fossil fuel power plants in regular demand periods is similar to the results in the first row of Table 2.3. However, none of the coefficient estimates in the placebo time frame is statistically significant. This points out that wind energy did not have a significantly differential impact on electricity generation from fossil fuel power plants from March 15 to May 31, 2019, compared with the period preceding it.

2.6.2 Merit-order effect

When we look at the merit order effect of rapid expansion of wind energy share in the grid, we see that the estimation results align with theoretical expectations. Table 2.5 reports the results for the estimation of Equation 2.1, with $\ln(P_h)$ as the dependent variable. The coefficient of interest, β , provides the estimate for the elasticity of day-ahead market prices to wind energy during and prior to the negative demand shock. Estimates in the first row of Table 2.5 indicate that a 1% increase in electricity generated in wind power plants reduces day-ahead market prices by 0.19%, on average. During COVID-19 lockdowns, this short-term price effect attenuates. A 1% increase in wind energy decreased electricity prices by approximately 0.14% during the negative demand

shock, a figure 0.05% lower than that during regular demand periods.

The merit-order effect of wind energy even more severely attenuates in periods with a higher reduction in aggregate demand. As shown in Table 2.6 Column (2), the coefficient estimate for β for the late COVID period is higher than the coefficient estimate for the early COVID period, although the difference is not large (approximately 0.7%). Assuming that the demand curve is shifting around the flatter part of the merit-order curve by within-day variations in aggregate consumption, this finding conforms to the theoretical expectations.

I analyze the percent changes in the day-ahead market prices in US dollars. Due to frequent use of fuels, equipment and machinery imported with foreign currency and feed-in tariffs for electricity generation from renewables paid in USD, producers might be relying more on USD for their production decisions than TRY. Yet, the decision to use USD for this analysis might be questionable given that the local currency is not pegged to USD. To address these concerns, I also run the analysis with TRY in real terms. When we change the currency of the dependent variable in equation 2.1 from USD to TRY, both in real terms, the results do not change. Table A2.1 shows the estimation results for real TRY in logs as the dependent variable, confirming that the results are in line with the theoretical expectations.

As a robustness check, I examine if wind energy had a similar merit-order effect in years preceding 2020 during March 15 - May 31 period. For this, I again use the placebo treatment period of March 15 - May 31, 2019 and January 1, 2016 - March 14, 2019 period as the alternative control period. I present the results of the placebo test for the merit-order effect in Table 2.7. In column (3), we see that the interaction term is insignificant at conventional significance levels, indicating that wind energy did not have a differential impact on day-ahead market spot prices between the placebo treatment period in 2019 and the period before it.

2.6.3 GHG emissions and damages

The substantial decrease in aggregate electricity consumption during COVID-19 lockdowns suggests an overall drop in GHG emissions. However, the negative demand shock changed not only the overall demand but also the load profile and variance of the within-day electricity consumption. According to Figure 2.9, the within-day variance increased and the load profile of weekdays resembled that of weekends during lockdowns, as the share of residential consumption increased during this period. The cycling power plants in Turkey are natural gas power plants, which are cleaner than lignite power plants providing the baseload. So, the increase in variance could have resulted in lower emissions as suggested by Holland and Mansur (2008). However, the overall decrease in demand shifted cycling power plants from natural gas to coal. Figure 2.10e shows the increased variance in production from coal power plants during COVID-19 lockdowns compared to the preceding period. This shift allowed wind energy to reduce generation from dirtier coal (and also lignite) power plants at higher levels compared to regular demand periods, as presented in Section 2.6.1. Therefore, I expect the rapid increase in RES to enhance wind energy's ability to diminish GHG emissions from fossil fuel power plants. Consequently, damages from carbon emissions should be curbed as well.

Results presented in Table 2.8 indicate that a 1% increase in electricity generated from wind power plants reduces CO₂ emissions by 0.03%, CH₄ emissions by 0.04%, N₂O emissions by 0.02%, and CO₂-equivalent GHG emissions by 0.027%, in regular demand periods. During the negative demand shock period, this effect is enhanced, and a 1% increase in electricity from wind energy results in an additional reduction of 0.036% for CO₂, 0.037% for CH₄, 0.039% for N₂O, and 0.037% for CO₂e emissions.

To assess the impact of a more substantial demand reduction on GHG reduction, I compare the early and late COVID lockdown periods using the same analysis above. Figure 2.13 presents the

results. Accordingly, wind energy reduces even more GHG emissions from fossil fuel power plants in the lowest-demand period.

The results of the robustness check employing the placebo treatment period are in Table 2.9. Here, changing the treatment to a placebo period should result in statistically insignificant coefficient estimates for the interaction variable. The second row in Table 2.9 shows that wind energy does not have a differential impact on GHG emission reductions from fossil fuel power plants from March 15 to May 31, 2019, compared to the preceding period.

Lastly, I also investigate the societal damages avoided by wind energy through the carbon emission reductions from fossil fuel power plants. To quantify the damages avoided, following Section 2.5, I use IWG (2021)'s SCC estimates with 3% discount rate for CO₂, CH₄ and N₂O for 2020 GHG emissions, which equals a mean value of \$51/tCO₂, \$1,500/tCH₄ and \$18000/tN₂O respectively. I estimate equation 2.1 using three dependent variables equal to hourly damages from a ton of CO₂, CH₄ and N₂O released to the atmosphere from fossil fuel power plants. The results of this model are in Table 2.10. In regular demand periods, 1 MWh of additional wind energy avoided \$17.02, \$7.53 and \$13.90 in damages from CO₂, CH₄ and N₂O. During the negative demand shock and rapid expansion of RES, an additional MWh of wind energy avoided \$7.14, \$1.29 and \$20.02 more in damages from CO₂, CH₄ and N₂O emissions than the regular demand periods. In total, in the presence of COVID-19 lockdowns, 1MWh of wind energy reduced \$24.16, \$8.82 and \$33.92 worth of hourly damages from CO₂, CH₄ and N₂O respectively. The substantially higher reduction in damages from N₂O during COVID-19 lockdown period should be related to wind energy's impact on displacing more coal energy during this period compared to the regular demand period.²⁸

All coefficient estimates explained in this section are statistically significant at the 0.01% level,

²⁸Coal is the primary source of nitrous oxide emissions from stationary combustion. See EPA's overview of GHG emission sources, [link](#)

and all models include the full specification where the binary *Covid* variable is interacted with higher-order polynomials of hourly demand, $f(D_h)$. The size and significance of results do not change with different combinations of higher-order polynomials of hourly demand.

2.7 Discussion and Conclusion

Exploiting a unique natural experiment, I study the impact of a rapid expansion of the share of intermittent renewable energy on electricity market outcomes in a low environmental regulation setting. For my analysis, I used a novel dataset including the hourly generation of each power plant, aggregate demand, spot market prices, and GHG emissions from stationary combustion in electricity generation. With a unique identification strategy, I causally estimated the impact of a rapid expansion of wind energy share on generation from fossil fuel power plants, electricity prices, GHG emissions, and societal damages. I show that the negative demand shock during the Covid-19 period can be seen as analogous to a rapid expansion of renewable energy in the electricity grid and results in strengthening of the negative effect of wind energy on generation from dirtier fossil fuel power plants and damages from GHG emissions. But this expansion attenuates the price-depressing impact of wind energy in the spot electricity market.

Findings on the abatement of GHG emissions show that even with low environmental regulations, policies that boost installed capacity for renewable energy might be a powerful tool in climate change mitigation. This is especially crucial as installation costs of renewable energy sources are declining at an increasing rate.

While we can be cautious about the external validity of the findings in general, the merit-order effect of the expansion of highly variable and intermittent renewables might be encouraging for the future of the electricity markets. If the rapid expansion of renewable energy curtails the

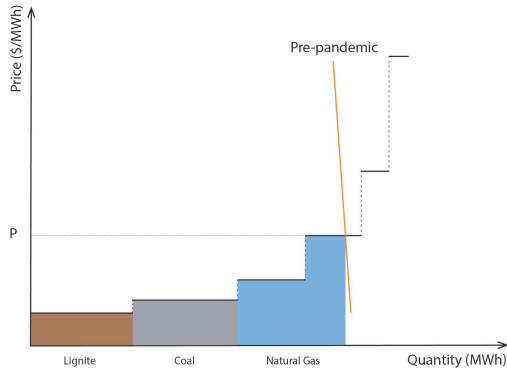
ability of zero marginal cost electricity generation to reduce electricity prices, then this might reverse the “cannibalization effect” (López Prol et al. 2020), i.e., the argument that the high penetration of renewable energy undermines its own value as it depresses wholesale and spot prices to unsustainable levels. If this could be reversed with the rapid expansion of renewables, it would eliminate an important roadblock for grid operators and policymakers to plan for the integration of renewables into the grid.

Future research would benefit from expanding similar analyses to other contexts with different types of grid operators and environmental regulations for examining the external validity of the findings in this paper. In contexts where environmental regulations increase the marginal cost of using high carbon-content fuels in electricity generation (namely, coal and lignite), the findings in this research project might be quite different as the merit-order curve sequencing would be different than in Turkey’s electricity grid.

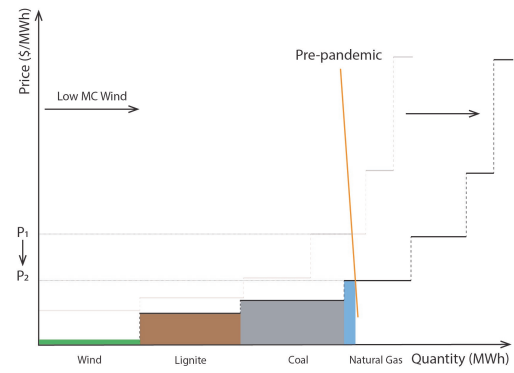
Finally, this study provides future researchers with the opportunity to extend Graf et al. (2021)’s analysis on re-dispatch costs and Davis and Hausman (2016)’s analysis on transmission constraints to the case of Turkey. Solutions to the optimization concerns of system operators under high reliance on intermittent renewable resources could be tested in this setting as well. Since the data used in this analysis are publicly available to researchers, these extensions should be a relatively straightforward exercise.

2.8 Figures and Tables

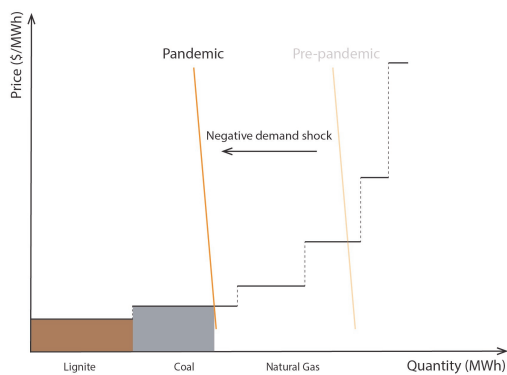
2.8.1 Figures



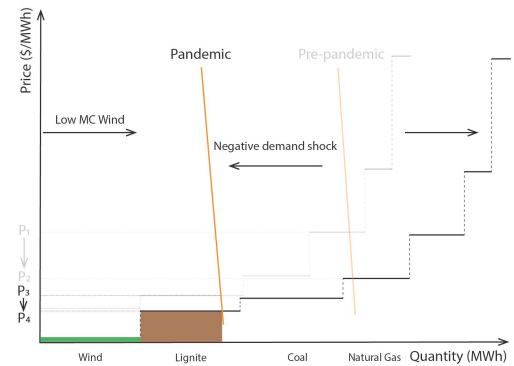
(a) Pre-pandemic average demand with no wind energy.



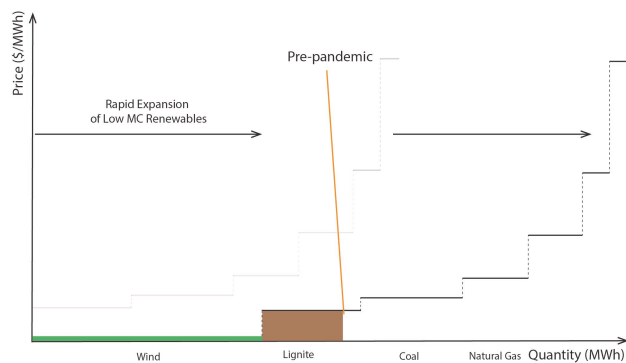
(b) Pre-pandemic average demand and the addition of low MC wind energy.



(c) Pandemic average demand with negative demand shock and no wind energy.



(d) Pandemic average demand with negative demand shock and addition of low MC wind energy.



(e) Rapid expansion of wind energy under pre-pandemic demand conditions.

Figure 2.1: Stylized explanation of the theoretical expectations.

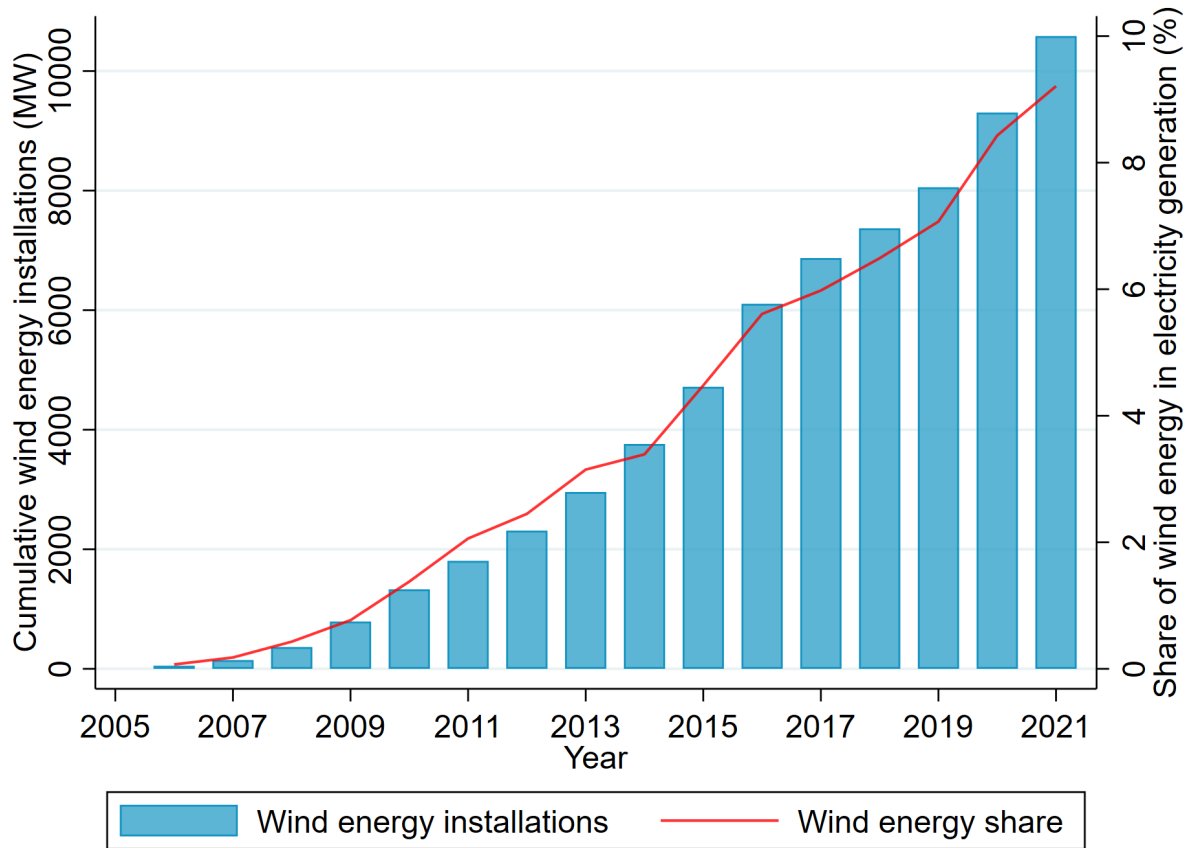


Figure 2.2: Expansion of wind power in Turkey between 2005-2021.

The blue bars show the increase in installed wind energy capacity starting with a mere 51MW in 2006 to 10,585MW in 2021. The red line shows the increase in the share of wind energy in annual aggregate electricity generation in Turkey. The share of wind energy was only 0.07% of the aggregate electricity generation in 2006 and it increased to almost 10% in 2021. (Source: [TUREB Wind Energy Powerplants Database](#), TUREB (2020))

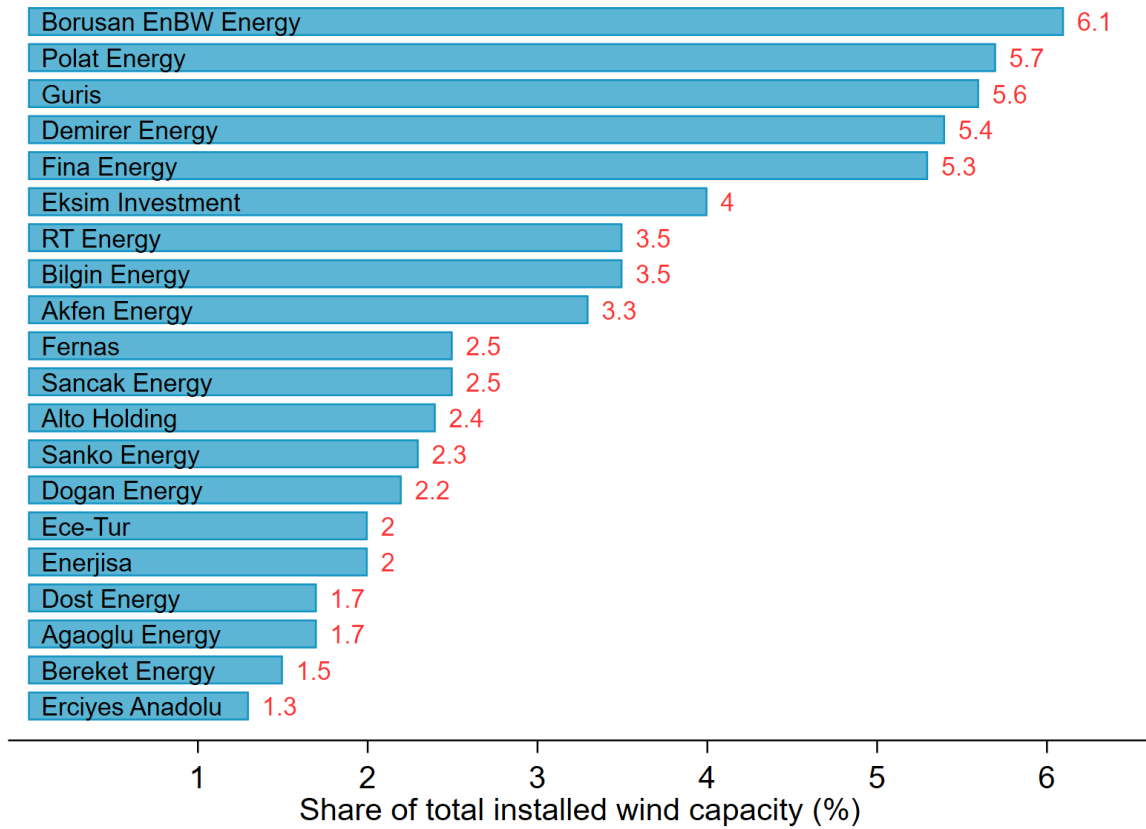


Figure 2.3: Installed wind energy capacity share (in %) of the top 20 firms operating in wind energy sector in 2020. Remaining companies outside of the top 20 comprise approximately 35% of the installed wind energy capacity. (Source: [TUREB Wind Energy Powerplants Database](#))



Figure 2.4: Average daily electricity generation in 2019 and 2020.

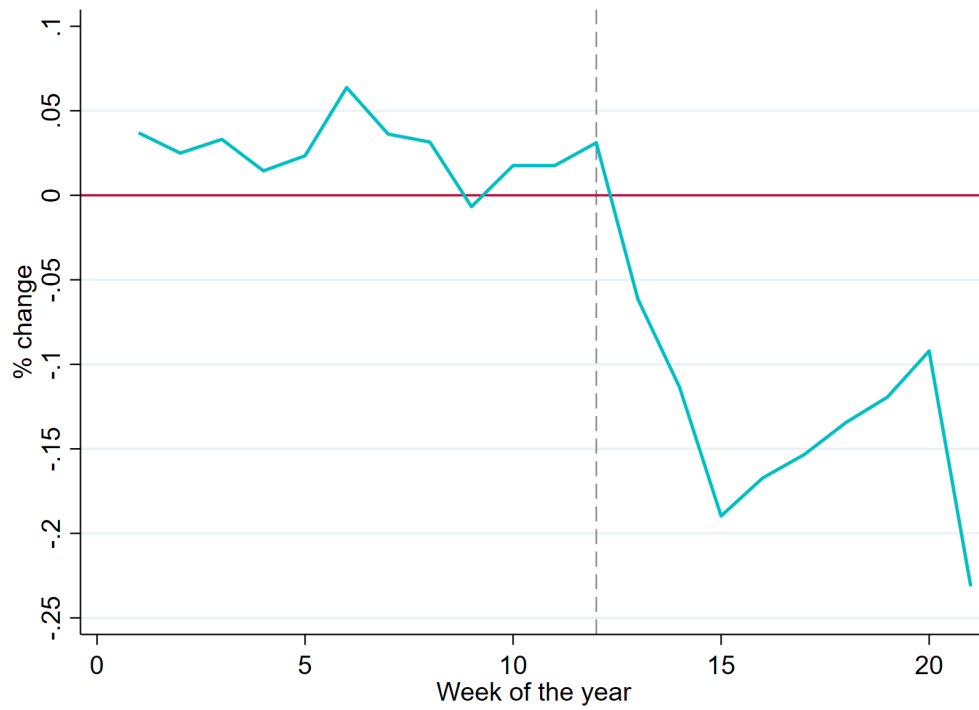


Figure 2.5: Change between 2020 and 2017-2019 average weekly electricity production.

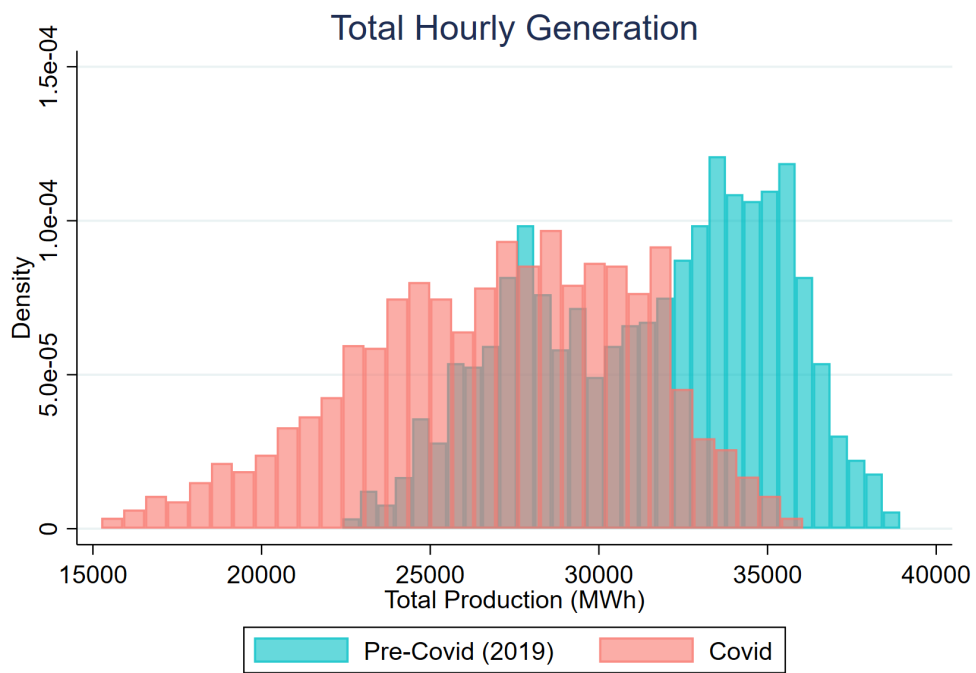


Figure 2.6: Distribution of electricity generation during Covid-19 lockdowns (March 21 - May 31 2020) and the same period in 2019.

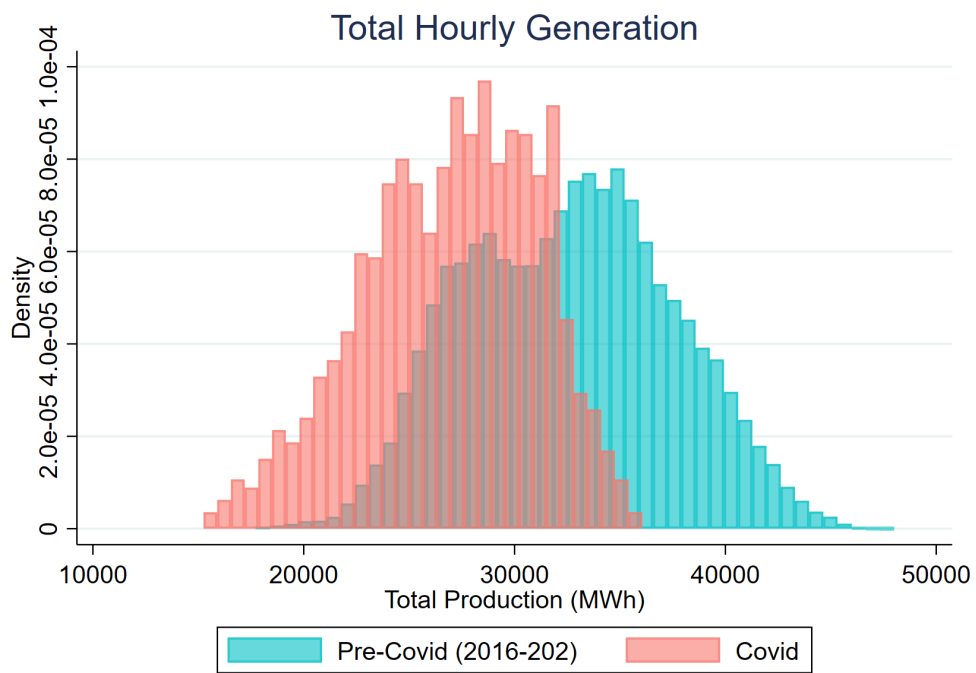


Figure 2.7: Distribution of hourly electricity generation during Covid-19 lockdowns (March 21 - May 31 2020) and period preceding it.



Figure 2.8: Average day-ahead market price in USD/MWh by week of the year before and during Covid-19 lockdowns.

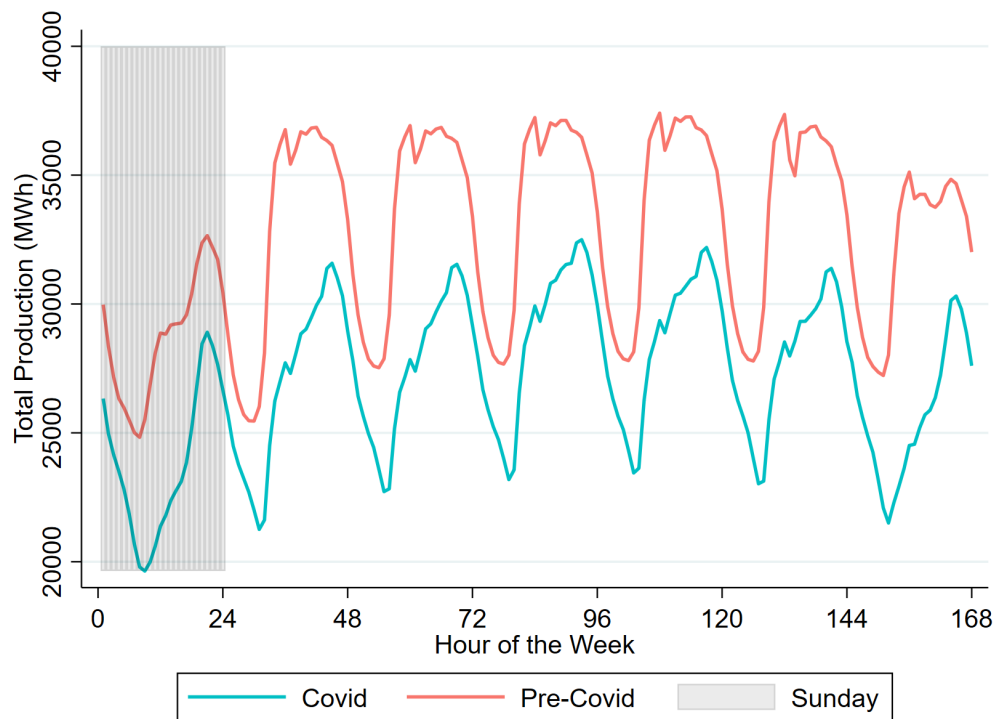
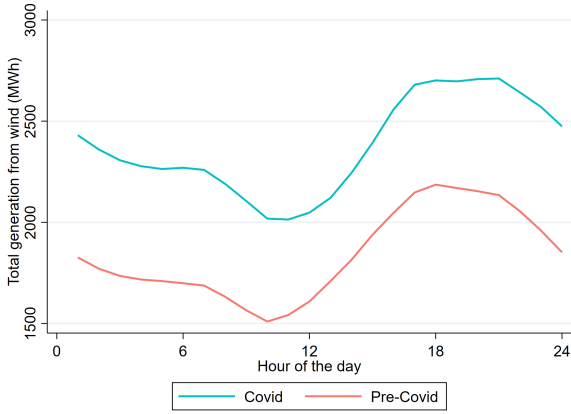
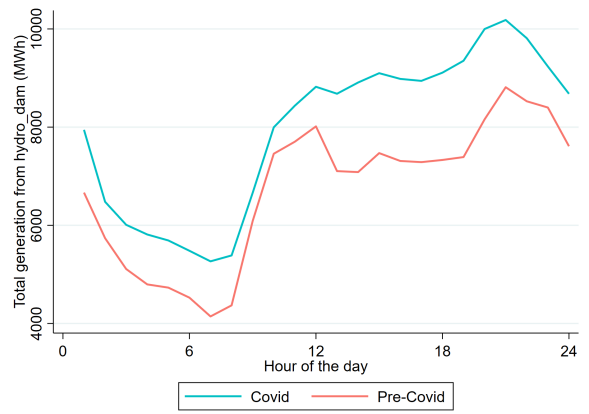


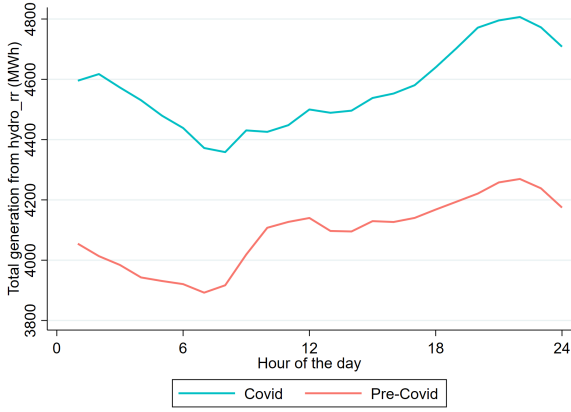
Figure 2.9: Average total energy consumption by hour of the week before and during Covid-19 lockdowns.



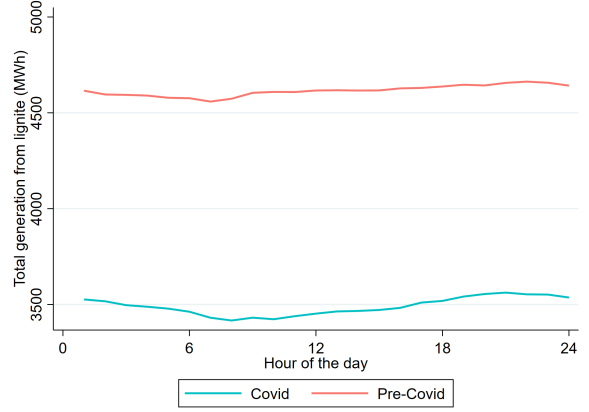
(a) Wind



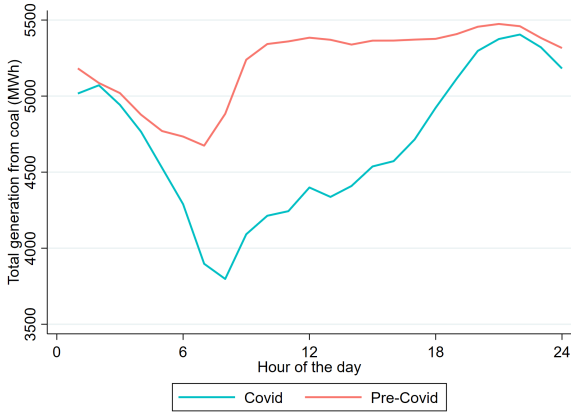
(b) Hydropower Dam



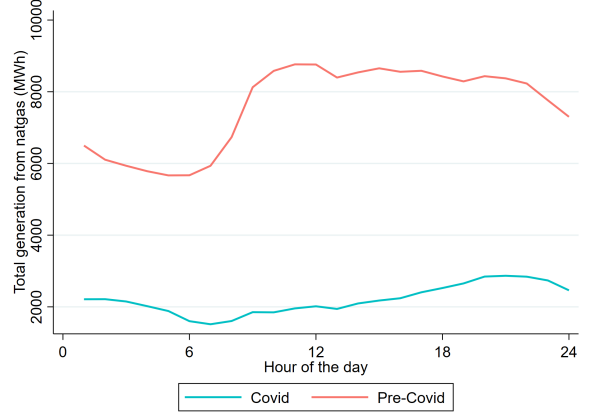
(c) Hydro RoR



(d) Lignite

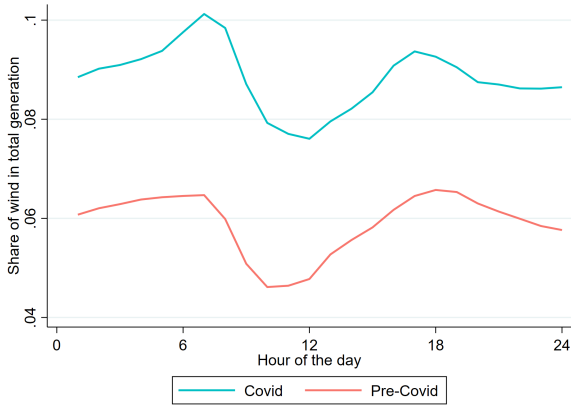


(e) Coal

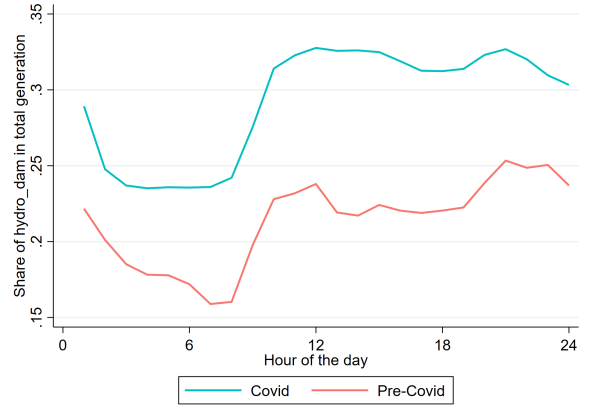


(f) Natural Gas

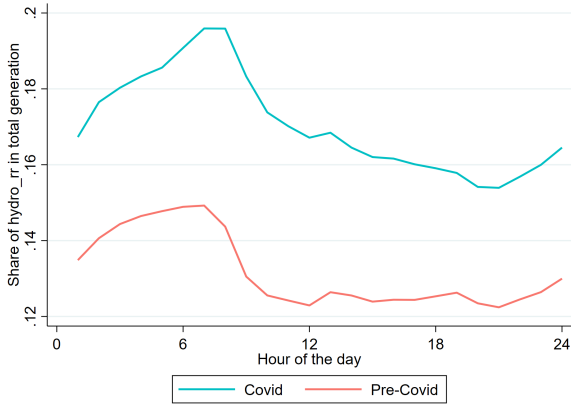
Figure 2.10: Change in average hourly generation by fuel type before and during negative demand shock



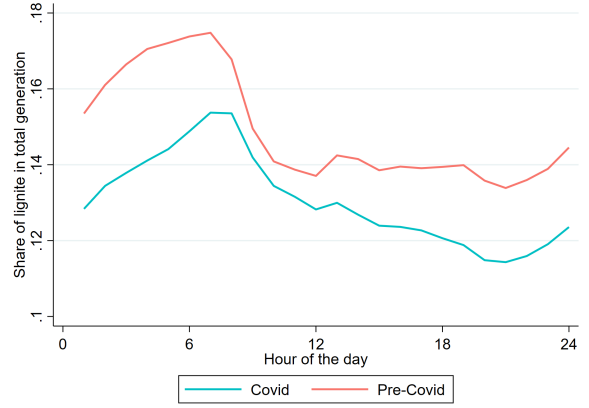
(a) Wind



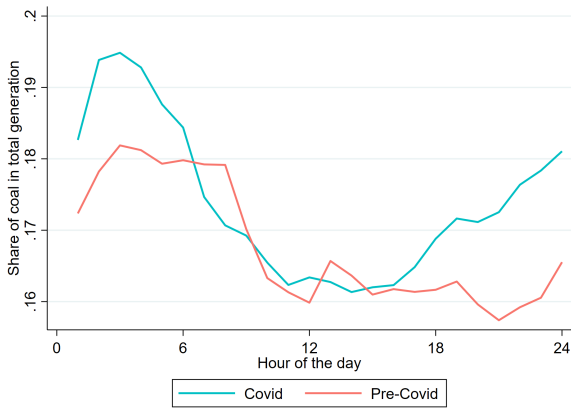
(b) Hydropower Dam



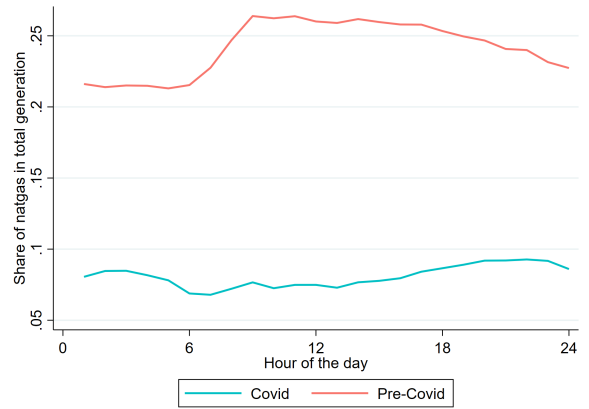
(c) Hydropower RoR



(d) Lignite



(e) Coal



(f) Natural Gas

Figure 2.11: Change in average hourly share of total generation by fuel type before and during negative demand shock

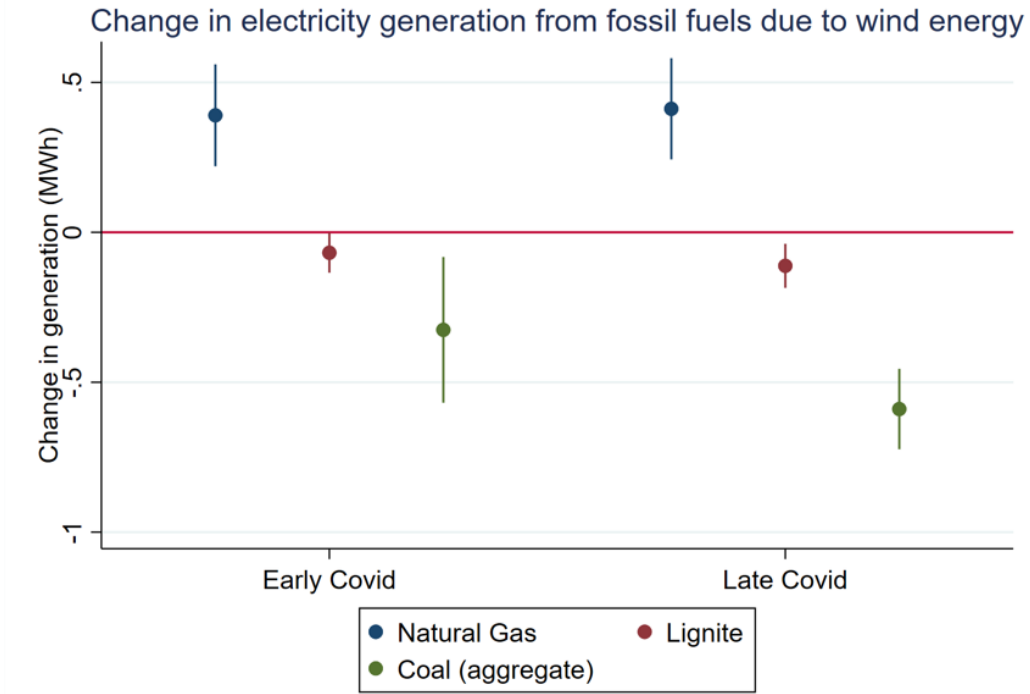


Figure 2.12: Change in electricity generation from fossil fuels due to wind energy

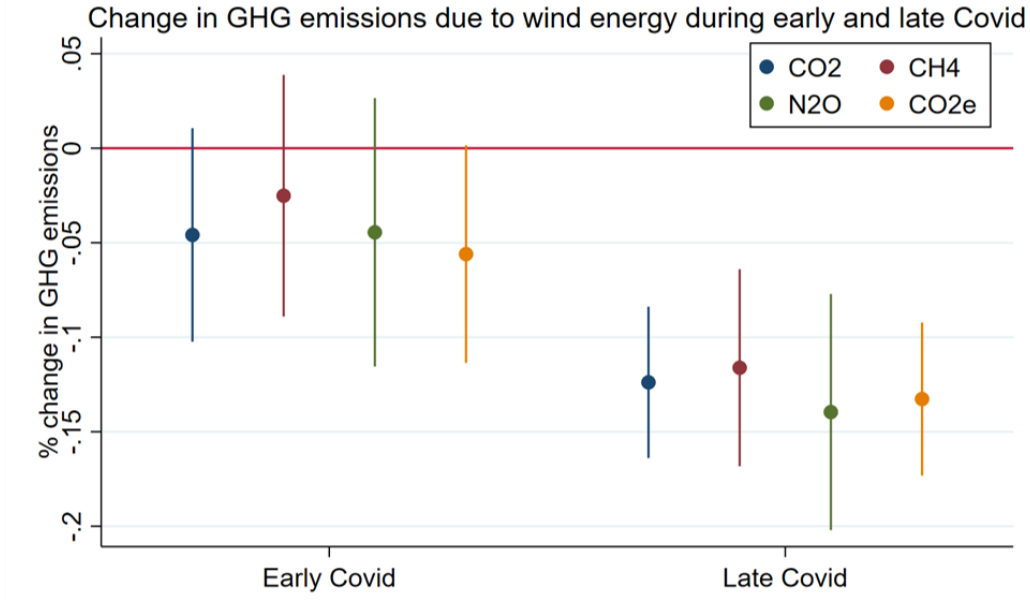


Figure 2.13: Change in GHG emissions from fossil fuels due to wind energy

2.8.2 Tables

Table 2.1: Summary Statistics for the whole sample

Variables	(1) Mean	(2) SD	(3) Min	(4) Max
Aggregate generation (MWh)	32361	5015.75	15247	48009
Day-ahead market price (real TRY/MWh)	64.91	22.64	0.00	743.4
Day-ahead market price (real US\$/MWh)	45.55	15.12	0.00	542.0
<i>Generation from renewables (MWh)</i>				
Wind	2186	1312.75	24.31	6322.91
Hydro (dam)	5777	2733.00	168.61	14239.84
Hydro (run-of-river)	2324	1305.90	343.39	7077.03
Solar	10.25	24.24	-1.70	177.41
Geothermal	740.29	219.92	308.95	1199.35
Biomass	269.39	88.86	112.15	485.13
<i>Generation from fossil fuels (MWh)</i>				
Natural gas	9305	3962.65	496.66	19134.33
Coal (aggregate)	6893	1600.91	1296.73	9722.17
Coal (imported)	6289	1574.20	986.10	8832.19
Coal (asphaltite)	278.84	81.94	0.00	545.35
Coal (anthracite)	325.21	80.03	61.50	622.50
Lignite	4738	701.88	2189.10	7339.27
Fuel-oil	146.96	63.43	0.00	393.34
Oil	0.00	0.00	0.00	0.00
LNG	1.28	3.04	0.00	19.20
<i>GHG Emissions (tonnes/h)</i>				
CO ₂	14.70	2.85	3.82	20.48
CH ₄	0.18	0.04	0.04	0.27
N ₂ O	0.06	0.01	0.02	0.08
CO ₂ eq	36.58	6.76	10.19	49.67

Table 2.2: Summary Statistics for different panels of the sample

VARIABLES	(1)	(2)	(3)	(4)
	Covid19 Lockdowns (March 15, 2020- May 31, 2020)	Pre-Covid19 Lockdowns (January 1, 2016 - March 14, 2020)	Covid19 in 2019 (Placebo) (March 15, 2019 - May 31, 2019)	Pre-Covid19 Lockdowns (3 months) (December 15, 2019 - March 14, 2019)
Aggregate Generation (MWh)	26971.45 (4117.07)	32613.63 (4911.34)	31260.86 (4149.15)	34350.80 (4546.29)
Day-ahead market price (TRY/MWh)	49.82 (26.28)	65.62 (22.20)	55.24 (29.51)	74.37 (15.74)
Day-ahead market price (\$/MWh)	29.19 (15.42)	46.32 (14.67)	34.06 (18.28)	48.34 (10.43)
Generation from wind (MWh)	2376.78 (1403.98)	2177.33 (1307.67)	2071.04 (1270.47)	3230.89 (1526.50)
Generation from hydro (dam) (MWh)	7957.28 (2077.72)	5675.95 (2717.43)	9529.63 (2120.55)	6850.27 (2804.31)
Generation from hydro (RoR) (MWh)	4567.64 (502.91)	2219.47 (1235.80)	4586.09 (905.76)	2522.15 (1105.15)
Generation from solar (MWh)	46.01 (56.65)	8.58 (20.07)	20.94 (25.32)	24.42 (38.20)
Generation from natural gas (MWh)	2194.45 (1114.41)	9637.21 (3729.15)	4048.9 (1802.97)	7221.61 (3227.69)
Generation from coal (MWh)	4685.24 (1615.17)	6996.62 (1523.98)	4893.42 (1432.77)	8463.07 (851.30)
Generation from lignite (MWh)	3490.44 (417.56)	4797.05 (656.76)	4842.23 (471.96)	4389.19 (633.82)
Aggregate CO ₂ emissions (tonnes/h)	8.61 (1.93)	14.99 (2.55)	11.05 (2.13)	14.95 (2.09)
Aggregate CH ₄ emissions (tonnes/h)	0.09 (0.02)	0.18 (0.03)	0.12 (0.03)	0.18 (0.03)
Aggregate N ₂ O emissions (tonnes/h)	0.04 (0.01)	0.06 (0.01)	0.05 (0.01)	0.06 (0.01)
Aggregate CO ₂ eq emissions (tonnes/h)	22.92 (5.05)	37.22 (6.12)	28.76 (5.34)	38.33 (4.54)

Table 2.3: Generation Offset by Fuel Type

	(1)	(2)	(3)
VARIABLES	Natural Gas	Lignite	Coal
Wind	-0.5265*** (0.0060)	-0.0131*** (0.0017)	-0.1251*** (0.0034)
Wind \times Covid	0.2069*** (0.0259)	-0.0248*** (0.0074)	-0.2156*** (0.0146)
$f(D) \times Covid$	Yes	Yes	Yes
Observations	38,710	38,710	38,710
R-squared	0.9893	0.9719	0.9793

Dependent variable is the hourly generation from fossil fuel power plants in MWh. Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

Table 2.4: Generation Offset by Fuel Type - Placebo

DV: Hourly generation from fossil fuel power plants (MWh)

	(1)	(2)	(3)
VARIABLES	Natural Gas	Lignite	Coal
Wind	-0.5587*** (0.0071)	-0.0071*** (0.0020)	-0.1397*** (0.0038)
Wind \times Covid	0.1188 (0.3221)	-0.0199 (0.0924)	-0.0622 (0.1736)
$f(D) \times Covid$	Yes	Yes	Yes
Observations	29,926	29,926	29,926
R-squared	0.9874	0.9579	0.9742

The results in this table is the placebo test for the results in Table 2.3. Covid treatment variable is coded as the period between March 15 - May 31 2019. Dependent variable is the hourly generation from fossil fuel power plants in MWh. Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

Table 2.5: Merit order effect of wind energy

	(1) Pre-Covid19	(2) Full Panel	(3) Full Panel
Ln(Wind)	-0.1932*** (0.0131)	-0.1931*** (0.0137)	-0.1933*** (0.0137)
Ln(Wind) \times Covid		0.0537*** (0.0147)	0.0507*** (0.0150)
$f(Ln(D)) \times$ Covid	No	No	Yes
Observations	36,982	38,710	38,710
R-squared	0.7479	0.7632	0.7639

Dependent variable is the natural log of hourly price of 1 MWh of electricity in the day-ahead markets in US dollars.

Newey-West standard errors with 24 hours lag are in parentheses. For statistical significance, *** p<0.01, ** p<0.05, * p<0.1.

Table 2.6: Merit Order Effect of Wind Energy - Early vs Late Lockdown

VARIABLES	(1) Full-Panel	(2) Full-Panel
Ln(Wind)	-0.1932*** (0.0137)	-0.1936*** (0.0136)
Ln(Wind) \times Early Covid ¹	0.0285*** (0.0089)	0.0461*** (0.0091)
Ln(Wind) \times Late Covid ²	0.0770*** (0.0087)	0.0534*** (0.0092)
$f(Ln(D)) \times$ Covid	No	Yes
Observations	38,710	38,710
R-squared	0.7633	0.7650

Dependent variable is the natural log of hourly price of 1 MWh of electricity in the day-ahead markets in US dollars.

¹ Early Covid is the period between March 15 - April 20, 2020.

² Late Covid is the period between April 21 - May 31, 2020
Newey-West standard errors with 24 hours lag are in parentheses. For statistical significance, *** p<0.01, ** p<0.05, * p<0.1.

Table 2.7: Merit order effect of wind energy - Placebo

	(1) Pre-Covid19	(2) Full Panel	(3) Full Panel
Ln(Wind)	-0.1955*** (0.0146)	-0.1978*** (0.0158)	-0.1983*** (0.0158)
Ln(Wind) \times Covid		-0.2337 (0.6801)	-0.2429 (0.6855)
$f(Ln(D)) \times$ Covid	No	No	Yes
Observations	28,198	29,926	29,926
R-squared	0.7148	0.7420	0.7422

The results in this table is the placebo test for the results in Table 2.5. Covid treatment variable is coded as the period between March 15 - May 31 2019. Dependent variable is the natural log of hourly price of 1 MWh of electricity in the day-ahead markets in US dollars. Newey-West standard errors with 24 hours lag are in parentheses. For statistical significance, *** p<0.01, ** p<0.05, * p<0.1.

Table 2.8: Change in GHG emissions

VARIABLES	(1) Ln(CO ₂)	(2) Ln(CH ₄)	(3) Ln(N ₂ O)	(4) Ln(CO ₂ e)
Ln(Wind)	-0.0320*** (0.0005)	-0.0396*** (0.0006)	-0.0191*** (0.0006)	-0.0268*** (0.0005)
Ln(Wind) × Covid	-0.0361*** (0.0055)	-0.0366*** (0.0059)	-0.0394*** (0.0057)	-0.0374*** (0.0056)
<i>f(Ln(D))</i> × Covid	Yes	Yes	Yes	Yes
Observations	38,710	38,710	38,710	38,710
R-squared	0.9903	0.9912	0.9855	0.9887

Dependent variable is the natural log of hourly GHG emissions (CO₂, CH₄, N₂O) from fossil fuel power plants in MWh.

Newey-West standard errors with 24 hours lag are in parentheses. For statistical significance, *** p<0.01, ** p<0.05, * p<0.1.

Table 2.9: Change in GHG emissions - Placebo

VARIABLES	(1) Ln(CO ₂)	(2) Ln(CH ₄)	(3) Ln(N ₂ O)	(4) Ln(CO ₂ e)
Ln(Wind)	-0.0311*** (0.0006)	-0.0381*** (0.0007)	-0.0188*** (0.0006)	-0.0262*** (0.0006)
Ln(Wind) × Covid	-0.0089 (0.0232)	-0.0106 (0.0335)	-0.0091 (0.0235)	-0.0087 (0.0233)
<i>f(Ln(D))</i> × Covid	Yes	Yes	Yes	Yes
Observations	29,926	29,926	29,926	29,926
R-squared	0.9887	0.9894	0.9833	0.9870

Dependent variable is the natural log of hourly GHG emissions (CO₂, CH₄, N₂O) from fossil fuel power plants in MWh.

Newey-West standard errors with 24 hours lag are in parentheses. For statistical significance, *** p<0.01, ** p<0.05, * p<0.1.

Table 2.10: Change in Social Benefits

VARIABLES	(1) Damages CO2	(2) Damages CH4	(3) Damages N2O
Wind	-17.0198*** (0.1934)	-7.5286*** (0.0738)	-13.9006*** (0.3262)
Wind \times Covid	-7.1441*** (0.8389)	-1.2893*** (0.3200)	-20.0254*** (1.4151)
$f(D) \times$ Covid	Yes	Yes	Yes
Observations	38,710	38,710	38,710
R-squared	0.9916	0.9924	0.9867

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent variables are the hourly damages in US\$ per ton of CO₂, CH₄ and N₂O emissions from fossil fuel power plants. Hourly damages are calculated using the IWG's SCC estimate for 2020 CO₂, CH₄ and N₂O emissions with 3% discount rate.

Newey-West standard errors with 24 hours lag are in parentheses. For statistical significance, *** p<0.01, ** p<0.05, * p<0.1.

Chapter 3

ASYMMETRIC PRICE RESPONSE OF OIL SUPPLY

3.1 Introduction

Understanding how oil producers respond to fluctuations in oil prices is often of great interest to policymakers. For instance, the impact of environmental policies affecting oil demand or supply (e.g. taxes/subsidies to oil production, EV subsidies, biofuel subsidies), including the resulting market equilibria and the incidence on consumers and producers, depends crucially on the price elasticity of supply for oil. Finding this elasticity is also important in understanding the underlying mechanisms and designing policies that help reduce oil price volatility.

Existing literature on this policy-relevant issue suggests that oil production levels are highly price inelastic. While some recent papers consider differences between conventional (vertically drilled) and unconventional (horizontally drilled) wells, micro-level evidence spanning a wide range of years including post-fracking boom years (mid-2000s onward) remains scarce.

In addition, to the best of our knowledge, there appears to be no literature analyzing the possibility of asymmetric effects on oil supply of increases and decreases in prices. Regarding asymmetric responses, previous papers focus on effects on oil and gas demand using macro-level data, and find suggestive evidence of asymmetries. In explaining the asymmetric consumption responses, these papers point to the fact that investment on energy-using equipment involves large sunk costs and is often irreversible.

A similar feature may apply in the case of oil production as well. Drilling a new well involves

large costs, especially for non-conventional wells. Furthermore, due to geological constraints, once a well is tapped, altering production levels are costly, particularly in the case of conventional wells. Finally, the fact that non-conventional wells have higher decline rates and shorter lifespan may also induce different responses among different types of wells. It is therefore of empirical interest to carefully examine asymmetries in price elasticity of supply for both conventional and non-conventional wells using micro-level data. Such an analysis could potentially yield significant policy implications; if asymmetries in supply responses exist, then ignoring this asymmetric response will bias general estimates of price elasticity of supply for oil, thereby implying that previous estimates should be treated with caution.

In this paper we examine well operators' oil supply response to oil price increases and decreases. Particularly, in this paper we investigate if asymmetries exist in oil supply responses to changes in price distinguishing between conventional and unconventional wells. We use monthly well-level data from approximately 18,000 unconventional and 5,000 conventional wells drilled in North Dakota between January 1990 and December 2021.

We find that in unconventional wells drilled with horizontal drilling and hydraulic fracturing, oil supply responds to price changes. A 1% price increase in oil prices is associated with 0.022% increase in contemporaneous oil production and a 1% decrease in oil prices is associated with a 0.08% decrease in contemporaneous oil production. The difference between these two supply elasticities is also statistically significant, indicating an asymmetric price response in oil supply in unconventional wells. For conventional wells drilled vertically, we did not find a significant oil supply response to changes in oil prices, which is in line with the findings in the literature focused on the supply elasticity of oil supply in conventional wells.

The paper's main contribution to the literature is that it carefully combines the traditional

literature on asymmetric responses to price changes with recent empirical literature relating to price elasticity of supply for oil. First, regarding the former wave of literature, the paper shifts the focus of the analysis from asymmetric price elasticity of energy demand to energy supply. Previous literature predominantly focused on the asymmetry of natural gas, oil or gasoline prices on energy demand. This project aims to understand how producers respond to oil price volatility by adjusting their oil supply. As such, the paper equally sheds a new light on the asymmetric supply response literature by using micro-level evidence (as opposed to macro-level analyses widely adopted in this literature) and by incorporating geological characteristics of oil production. Second, the paper provides valuable findings to the emerging literature on price elasticity of supply for oil, by examining the possibility of asymmetric responses using granular, well-level monthly oil production data.

The paper is organized as follows: Section 3.2 provides an overview of the literature on oil supply elasticity and asymmetric price response in oil and gas markets. Section 3.3 gives background information on oil production processes in unconventional horizontally drilled wells and conventional vertically drilled wells. Sections 3.4 and 3.5 introduce the empirical methods and data we used to answer the research questions for this project, and Section 3.6 presents the findings. The paper concludes with a discussion about policy implications and suggestions on future research in Section 3.7.

3.2 Existing literature

The conceptual framework of Hotelling (1931), where owners of exhaustible resources equate the marginal values of extraction across time, implies that production of such commodities should

increase when price increases.¹ However, in the case of oil, recent findings tend to suggest that production levels do not respond to prices, pointing to elasticity estimates that are close to zero and/or not statistically different from zero ([Anderson et al. 2018](#), [Dahl and Yücel 1991](#), [Ramcharan 2002](#), [Rao 2018](#)). In particular, [Anderson et al. \(2018\)](#) and [Bjornland et al. \(2017\)](#) offer theory and micro-level empirical evidence that production rates from existing wells are physically or geologically constrained and do not respond to prices, and that producers respond to prices by adjusting the rate of drilling new wells (with an elasticity of drilling of roughly 0.7). [Newell and Prest \(2019\)](#) also look at the price responsiveness of US conventional and unconventional oil supply at drilling, completion and production stages; and find similar results (i.e, higher elasticities at the drilling stage). While their observations are at the quarterly level and not at the monthly level, the geographical coverage (Texas, North Dakota, California, Oklahoma and Colorado) of their study is broad.

Nevertheless, well-level evidence on how oil production responds to prices are still rare. Many papers do not seem to adequately cover the period after which hydraulic fracturing (fracking) and horizontal drilling technologies became widely available (mid-2000s onward), and do not clearly distinguish between conventional wells and unconventional shale wells.

In particular, existing papers do not seem to examine the possibility of asymmetric effects on oil supply of increases and decreases in prices. Regarding asymmetric responses, previous papers focus on the effects of oil price changes on oil and gas demand using macro-level data ([Gately and Huntington 2002](#)). They find that oil demand response to a price increase is not necessarily reversed symmetrically by an equivalent price decrease. These papers point to the fact that energy consumption is closely related to the capital stock for energy-using equipment. For instance, when

¹For an overview of the Hotelling model see: [Slade and Thille \(2009\)](#)

oil prices go up, investment in retrofitting, such as building insulation, increases. However, given the large sunk costs, such retrofitting is often not reversed when oil prices decline. [Griffin and Schulman \(2005\)](#) questioned [Gately and Huntington \(2002\)](#)'s approach by underlining that it only captures the energy saving technology advances. In response, [Huntington \(2006\)](#) showed that for aggregate energy and oil demand both asymmetric price response and exogenous energy saving technical change play a role ([Adeyemi et al. 2010](#)).

A similar feature of capital stock impact may also hold in the case of oil production for both conventional and unconventional wells, possibly at different magnitudes. First, drilling a new well involves large costs, especially for unconventional wells. Second, recent empirical observations regarding shale oil production suggest that shale wells have higher decline rates than conventional wells ([Wachtmeister et al. 2017](#)). On a similar note, conventional wells have relatively uniform project economics and are long-life, allowing producers to make production decisions that are based on long-term oil price, while unconventional oil wells have more flexible production cycles and shorter lifespans, which may induce producers to respond more to short-term price changes ([Livingston 2014](#)). Finally, on the technology side, while the rate of production from a conventional well is physically constrained and altering production levels is very costly once tapped ([Anderson et al. \(2018\)](#)), shale wells are technologically more flexible and can be stimulated with water and chemicals many times during its lifetime, implying that production levels can be adjusted with more ease ([Bjornland et al. \(2017\)](#)).

It is therefore of empirical interest to carefully examine whether asymmetries exist in price elasticity of supply for both conventional and unconventional wells, using recent well-level data that reveal production decisions from both types of wells.

3.3 Background information

3.3.1 Oil production and shale technology

Before the widespread use of horizontal drilling and hydraulic fracturing technologies, geologists and oil and gas practitioners were aware of the fossil fuel reservoirs in shale formations. However, high costs involved in horizontal drilling and the hydraulic fracturing methods did not allow these reserves to be recovered efficiently. As costs dropped precipitously with the introduction of modern downhole motors and slickwater fracturing techniques, the oil and gas that has been trapped in shale formations started to be recovered economically in early 2000s.

The main determinant for the choice of technology (horizontal or vertical drilling) depends on the geology of the formation where oil is trapped. Conventional wells are quite efficient when oil reservoir is in porous and permeable formations such as sandstone. In these porous and permeable formations, a body of gas will gather at the top of the reservoir and oil will sit underneath it in porous rock. When a well is drilled vertically directly into this reservoir, the porous nature of the rock allows oil and gas in the reservoirs to flow naturally into the wellbore with the pressure difference inside the formation and on the earth's surface connected by the vertical well (Devold 2013). In contrast to this natural flow in conventional wells, unconventional wells with horizontal drilling require hydraulic fracturing to stimulate tight shale oil and gas resources to flow into the wellbore and then to the earth's surface, which we explain below (Newell et al. 2019).

Shale oil reservoirs are usually 1 mile or below the surface, which is similar to the conventional oil reservoirs. In Figure 3.1, we see that the vertical drilling can go as deep as 3000 meters, or approximately 2 miles. These depths could also be reached in conventional wells, so, the vertical drilling part is not different from the drilling process of conventional vertical wells. Yet, in contrast

to conventional reservoirs, where drilling is completed when the wellbore reaches the reservoir, shale oil reservoirs are trapped in thin layers of rock formations which is not economically feasible to pump oil with just the vertical part of wellbore reaching the reservoir. For the specific case of North Dakota, the middle Bakken geological layer, in which the majority of the oil reserves are stored, has a thickness of approximately 50 meters (150 feet) and has very low permeability, which makes it unsuitable for vertical drilling (Kuhn et al. 2012, Meissner 1984). Hence, to recover the oil in shale reservoirs the well should be drilled further at an angle. Following the vertical drilling, the wellbore is drilled horizontally which can extend several miles. When the horizontal drilling stage is completed it is first enforced with a casing to avoid collapsing of the horizontally drilled segment of the well. Then, a perforating gun is used to create perforation holes in the horizontal segment of the wellbore (Perforation Stage in Figure 3.1). These holes connect the oil reservoir and the wellbore. Following perforation, a mixture of water, sand, and chemicals are pumped into the wellbore creating long fractures in the perforated holes which bears the name hydraulic fracturing (Dirty Volume Stage in Figure 3.1). After fractures are opened, the water in the wellbore is pumped out and the sand in the mixture stays in the fractures to keep them open to facilitate the flowing of oil (or natural gas) into the wellbore (Closure Stage in Figure 3.1). This process is repeated along the horizontal segment of wellbore until all productive parts of the reservoir are fractured. When all the steps of horizontal drilling and hydraulic fracturing are completed, the pumping of remaining water mixture and flow of oil (or natural gas) with high pressure begins.

The initial flow of oil from unconventional wells is much higher than the conventional wells but as the effect of initial fracturing fades the perpetual decline in production is higher as well which can be seen in Figure 3.2. While the average unconventional or horizontal well in North Dakota reaches a maximum of almost 9000 barrels per month a few weeks after starting production, the

average conventional or vertical well could only reach to 2000 barrels per month on average. Yet, the rate of decline in an average unconventional well is much steeper than a conventional one. To increase production over the lifespan of an unconventional well, operators can repeat the fracturing process several times which creates a spiky production profile (Bjornland et al. 2017). This adds to the operating cost of the well and increases the marginal cost of producing oil in unconventional wells. The costly horizontal drilling and hydraulic fracturing processes cause the marginal cost of oil production and breakeven prices for unconventional wells to be substantially higher than conventional wells (Kleinberg et al. 2018). In 2013, the reported cost of fracking was in the range of \$2-5 million per well, out of the total average well cost of \$9 million (Covert 2015).

In addition to the differences in the drilling process, there are three important distinctions between conventional and unconventional oil production: aggregation of reservoirs, initial production levels and control over production levels (Newell et al. 2019). First, compared to conventional reservoirs, unconventional reservoirs are clustered in a single formation and uniformly distributed across that formation which prevents drilling too many dry holes. Second, both aggregate and initial production levels in unconventional wells are much higher than in conventional wells. Figure 3.2 illustrates this with respect to the oil wells in North Dakota spudded between 1990 and 2021.² Third, firms have control over the production in unconventional wells to a certain degree. This is not the case for conventional wells which work in terms of “tapping the keg” principle as (Anderson et al. 2018) show in their paper on the limited applicability of the Hotelling rule in conventional wells. The flexibility in unconventional wells allows operators to respond to price changes. We see the difference in production flexibility between conventional and unconventional wells in Figures 3.3 and 3.4. In Figure 3.3 we plot the average monthly production in vertically drilled conventional

²Spudding is the first step in the drilling process when the drilling bit starts drilling the surface hole.

wells in North Dakota against the WTI spot oil price. As clearly recognized in this plot, oil supply from conventional wells does not respond to price movements in global oil prices and is characterized with a steady decline over time. In Figure 3.4, we can discern that the average oil supply from horizontally drilled unconventional wells follows WTI spot oil price movements closely, especially after 2015 following the initial phase of the North Dakota shale oil boom between 2005-2015. Even though we do not examine the oil price elasticity of drilling in this paper, we see a similar pattern in oil price response of drilling conventional and unconventional wells. In Figures 3.5 and 3.6, we see that while the number of spudded conventional wells does not present a clear pattern with respect to oil price volatility, the number of new spudded unconventional wells explicitly follow the oil price movements.

3.3.2 ND oil sector and the shale boom

The first major oil discovery in North Dakota was in 1951 (Clarence Iverson farm in Williams county). Production slowly increased in the 1950s and 1960s as more oil was discovered. Spurred by the sustained high prices stemming from the two major global oil crisis due to the Yom-Kippur War of 1973 and the Iranian Revolution of 1979, the region experienced an oil boom in the 70s and early 80s with a surge in production and number of drilled wells. Production peaked at 150,000 barrels per day in 1984, and this period could be named as the “vertical” drilling boom in North Dakota. Yet both drilling rates and aggregate production quickly declined in the late 1980s following the fall in oil prices. The 1990s and early 2000s followed a gradual declining trend. Figure 3.7 shows the peak in the early 1980s and the gradual decline in the subsequent period for the oil production with vertical conventional wells.

Meanwhile, around 2002, the combined technology of horizontal drilling and hydraulic fracturing

(i.e., extended reach horizontal drilling) became available, allowing oil companies to extract oil and gas from the shale rock, as explained in the previous section. The discovery of the Parshall Oil Field in the Bakken Formation in 2006, coupled with the availability of this new technology, led to the rapid increase in shale oil production in North Dakota. The high oil prices in the 2000s before the 2007-08 financial crisis also contributed to the boom, offsetting the high costs associated with fracking and horizontal drilling ³. Figure 3.7 shows the extent of the shale oil boom in North Dakota with the spiking number of new wells after 2005. The combination of the introduction of cost effective methods for hydraulic fracturing and horizontal drilling with high oil and gas prices before the 2007-2008 financial crisis spurred the shale supply boom not only in North Dakota but in the U.S. as a whole (Hausman and Kellogg 2015, Kilian 2017). For instance, while shale oil provided 1% of U.S. oil production in 2000, it provided over 65% in 2021 (EIA 2022). The case for gas is even starker, while shale gas provided only 1% of U.S. natural gas production in 2000, it provided over 20% (Melek 2015) in 2010 and almost provided 80% in 2021.

As shown in Figures 3.8 and 3.9, North Dakota experienced a surge in both proven oil reserves and oil production from around 2005, much more so than its neighboring states Wyoming, and Montana and also other states on the Bakken Shale. In 2015, there were 10,619 active shale wells in North Dakota, and production from shale wells accounted for 95.7% of oil and gas production in the state. As of December 2021, North Dakota is producing approximately 1.13 million barrels of oil per day, which accounts for roughly 9.7% and 1.2% of U.S. and world oil production respectively ⁴. Figure 3.10 shows oil and gas producing counties in North Dakota. The state has 17 active oil and gas producing counties, with the core four counties of Williams, McKenzie, Dunn and Mountrail

³For more details on the history of North Dakota Oil Production, see e.g., [North's Dakota's official government website](#)

⁴See [North Dakota Oil and Gas statistics](#) and [EIA's crude oil production statistics](#)

accounting for at least 75% of total production. Figure 3.11 shows the locations of oil wells and it can be seen that most of the wells in North Dakota is concentrated in the core. This is in line with the geological characteristics of shale formations where oil reserves are clustered in a well defined area that does not allow the “hit and miss” drilling of dry wells, common in conventional oil reservoirs.

The high exposure to the shale boom and the recent prevalence of shale wells in addition to currently active conventional wells make North Dakota an ideal setting to investigate operators’ differential asymmetric oil well drilling and oil supply response in conventional and unconventional wells.

3.4 Empirical Methods

In this section, we present a graphical illustration of symmetric and asymmetric oil price response of production, the empirical models we use to test these hypotheses and the related hypotheses that we test.

The underlying assumptions for symmetric and asymmetric price response of oil supply can be illustrated with Figure 3.12.⁵ In the case of symmetrical response (shown in the bottom plot in Figure 3.12 with the title “Symmetric Response”), oil supply responds symmetrically to oil price changes and the supply-increasing response to a price increase in *Price boom 1* would be reversed by the supply-decreasing response to a price decrease in *Price slump*. In other words, the slopes of the lines would be the same for *Price boom 1* and *Price slump*. Also any price recovery following an oil price decrease would induce a similar supply reaction, meaning the slope for *Price boom 2* should be the same as the slopes of the other two lines. In contrast to this, in the case of asymmetrical

⁵The figure is adopted from Gately and Huntington’s (2002) paper on asymmetric price response of oil demand.

response (shown in the plot at the top of Figure 3.12 with the title “Asymmetric Response”) oil supply responds asymmetrically to oil price increases and decreases and the supply-increasing effect of an oil price increase in *Price boom 1* would not be reversed with a supply decrease of the same magnitude in response to an oil price decrease during *Price slump*. Hence, the slopes of the lines for *Price boom 1* and *Price slump* would not be the same. With regard to this graphical illustration, we will test the equality of the magnitude of oil supply responses to oil price increases and decreases in conventional and unconventional wells. We expect that in unconventional wells, (1) oil supply responds to oil price changes in statistically significant magnitudes and (2) the difference in oil supply response to oil price increases and decreases are significantly different from each other, indicating an asymmetrical price response. In conventional wells, we expect (1) oil supply not to respond to oil price changes and (2) the difference in oil supply response to price increases and decreases are not significantly different from each other.

To test these hypotheses, we run a model where we place the monthly production at the well level as the outcome variable and have the decomposed monthly oil price as price increases and decreases as predictors to estimate the separate effects of oil price increases and decreases on monthly production at the well level. We also use lagged dependent variables to control for the production of a well in previous months. We run this model separately for unconventional and conventional wells to discriminate the oil price elasticity of supply for wells drilled with different technologies. The model we estimate is below in equation 3.1:

$$\begin{aligned}
 IHS(Prod_{i,t}) = & \sum_{j=1}^k \beta_{prod_j} IHS(Prod_{i,t-j}) + \beta_{pc}^+ [IHS(Price_t) \times (PC_t^+)] + \gamma_{pc}^+ (PC_t^+) + \\
 & \beta_{pc}^- [IHS(Price_t) \times (PC_t^-)] + \beta_p IHS(Price_t) + \sum_{n=1990m1}^{2021m12} \eta_n month_n + \epsilon_{i,t}
 \end{aligned} \tag{3.1}$$

In this model we regress the hyperbolic sine transformed monthly oil production in each well on hyperbolic sine transformed monthly negative and positive oil price changes. We control for the oil production in each well in previous months. ⁶ $IHS(Prod_{i,t})$ is the hyperbolic sine transformed oil production in barrels in each well i , in each month t . $IHS(Prod_{i,t-j})$ are the lags of the dependent variable. In our main specification, j goes back three months, but we also try alternative specifications where j goes back as far as 12 months. $IHS(Price_t)$ is the hyperbolic sine transformed WTI spot oil prices at month t . PC_t^+ and PC_t^- are the binary variables to indicate positive or negative price change at month t . PC_t^+ is equal to one if the change in WTI spot oil price is positive from month $t-1$ to t , zero otherwise. PC_t^- is equal to one if the change in WTI spot oil price is negative from month $t-1$ to t , zero otherwise. We interact these two binary variables with the $IHS(Price_t)$ to estimate the price elasticity of oil supply in response to price increases and decreases at month t . Our coefficients of interest are β_{pc}^+ and β_{pc}^- . $month_n$ is the month dummy variable for all calendar months in the panel, from January 1990 to December 2021. It is equal to one for calendar month n and 0 otherwise. In total we add 383 month dummy variables in our model but since our panel has more than 2.5 million observations, it does not cause a problem for estimation. $\epsilon_{i,t}$ is the mean zero error term. To estimate the model we could have relied on several different options given its dynamic panel data structure with the inclusion of lagged dependent variables. The autoregressive nature of the model causes estimates to be biased when we use an OLS or regular two-way fixed effects estimator with well and month fixed effects, so we eliminate these options. To estimate this dynamic panel data model, we could use the GMM estimators created by Arellano and Bond (1991) (difference GMM) and Arellano and Bover Arellano and Bover (1995) and Blundell and Bond Blundell and Bond (1998) (system GMM), however these

⁶For a random variable x , taking the inverse hyperbolic sine transformation yields a new variable such that, $\tilde{x} = \text{arcsinh}(x) = \ln(x + \sqrt{x^2 + 1})$

estimators are suited for small T, large N samples. Our sample consists of 383 months, making it unsuitable for implementing difference and system GMM estimators. Instead of these options we first difference the model and use Anderson-Hsiao (AH) estimator ([Anderson and Hsiao 1982](#)).⁷ We include second and third lags of our dependent variable as instruments of the first lag of the dependent variable which will still be highly correlated with the lagged dependent variable but will be uncorrelated with the error term.

We also run a model with global macroeconomic indicators as control variables to examine if our model predicts the impact of global macroeconomic effects on oil production at the well level. The model we estimate is very similar to equation 3.1:

$$\begin{aligned}
 IHS(Prod_{i,t}) = & \sum_{j=0}^k \beta_{prod_j} IHS(Prod_{i,t-j}) + \beta_{pc}^+ [IHS(Price_t) \times (PC_t^+)] + \gamma_{pc}^+ (PC_t^+) + \\
 & \beta_{pc}^- [IHS(Price_t) \times (PC_t^-)] + \beta_p IHS(Price_t) + \gamma X_t' + \epsilon_{i,t}
 \end{aligned} \tag{3.2}$$

Different from equation 3.1, equation 3.2 includes X' , which contains the battery of macroeconomic control variables that might impact both oil production and also oil price changes. It includes MSCI All Countries World Index, U.S. 10 year treasury bond yield, trade weighted broad USD index, copper prices. Other variables are as described above for equation 3.1.

We also run our model where we have the natural logs of the variables instead of the hyperbolic sine transformation. This approach has a problem as there are quite a few zeros in production and price change variables. To be able to use these values, we added 0.001 to each observation of these variables that are equal to zero.

Concerning the causal interpretation of price elasticity, we have to consider the potential in-

⁷See a comment by Arellano [Arellano and Bond \(1991\)](#) on the AH estimator.

fluence of changes in North Dakota oil production on global oil prices. North Dakota accounts for 1.7% of global and 12% of U.S. oil production. Despite being cautious about potential reverse causality, changes in North Dakota oil production levels, production capacity and new well drilling might not substantially impact global spot or futures oil prices.

As mentioned above, in equations 3.1 and 3.2 our coefficient estimates of interest are β_{pc}^+ and β_{pc}^- . For asymmetric price response of oil production to hold, these two coefficient estimates should be different from each other at statistically significant levels. To test this we conduct a Wald test for the equality of these two coefficient estimates where the null hypothesis is that the sum of these two estimates are equal to or greater than zero. The alternative hypothesis is that the sum is less than zero, so we are running a one-sided test. The reason for this is related to the oil production process, especially in unconventional wells. While operators can shut off wells or decrease at later stages of a well's productive life, increasing production in productive wells is possible but quite expensive given the costs involved in re-fracking. Hence, we expect the absolute value of β_{pc}^+ estimate to be less than the β_{pc}^- estimate. We can define our hypothesis test as follows:

$$\begin{aligned} H_0 : \beta_{pc}^+ + \beta_{pc}^- &\geq 0 \\ H_1 : \beta_{pc}^+ + \beta_{pc}^- &< 0 \end{aligned} \tag{3.3}$$

For conventional wells, we expect estimates of β_{pc}^+ and β_{pc}^- to be statistically insignificant as it is quite costly to alter the production of conventional wells after the well starts producing oil. On the other hand, for unconventional wells, we expect estimates of β_{pc}^+ and β_{pc}^- to be statistically significant at conventional levels and the estimate of β_{pc}^+ to be less than β_{pc}^- which would allow us to reject the null hypothesis in equation 3.3.

3.5 Data

We use North Dakota Industrial Commission (NDIC) Oil and Gas Division’s monthly well-level data on oil production. The well-index from the NDIC has data starting from 1957, however the granularity and accuracy of the data are questionable before 1990, so we use the production data spanning from January 1990 to December 2021 in our analysis. This rich dataset includes information on location (county, file, latitude, longitude etc) and monthly oil production, water retention and gas release of each well, and company and field name the well is associated with. For our analysis, we will focus on the monthly oil production in each well. The technology used for drilling the well is also included in the dataset. So, we know which wells are drilled horizontally (with hydraulic fracking) and vertically from the data, which allows us to conduct our analysis separately for wells drilled using these two types of technology.

Summary statistics of the data we use in this paper is in Table 3.1. Our unbalanced panel has more than 1.6 million observations from unconventional (horizontal) wells, 1 million from conventional (vertical) wells. There are more than 2.8 million observations in total, but these include observations from dry wells and confidential wells, which we did not include in our analysis. The total number of wells is 17,699 for unconventional wells and 4,926 for conventional wells, which shows that more than 2/3 of wells were drilled using horizontal drilling and hydraulic fracturing. We see the difference in the average monthly oil production across unconventional and conventional wells in Table 3.1. While an average unconventional well produces approximately 2,500 barrels per month, an average conventional well produces below 500 barrels per month. This is in line with the general assumption that shale oil wells produce more oil on average than conventional wells.

For crude oil price data we use the monthly average of the Western Texas Intermediate (WTI) spot crude oil price for delivery in Cushing Oklahoma, New York Mercantile Exchange (NYMEX)

futures prices provided by the Energy Information Administration (EIA) ⁸. From Table 3.1 we can see that the WTI spot price and futures price for a 4-month contract on NYMEX have very similar mean and standard deviation values. Also, in Figure 3.13, we see that WTI spot, WTI 4-month futures and Brent spot prices follow each other pretty closely for the time frame of our analysis. So we can be assured that we can use WTI spot prices instead of the futures prices to measure the impact of oil price change on contemporaneous oil production. We did not use Brent spot prices for our analysis as it is not relevant for the producers in the U.S.

As mentioned in Section 3.4, we use several macroeconomic control variables for our alternative specification. The MSCI Index is the average monthly return of the MSCI All Country World Index (AWCI) that is publicly provided by MSCI. ⁹ The U.S. 10 year treasury yield is the market yield on U.S. Treasury securities at 10-Year constant maturity from St. Louis FED's economic database, FRED. ¹⁰ USD index is the nominal broad U.S. dollar index from FRED ¹¹ and the copper price is the global price of copper both from FRED. ¹²

3.6 Findings

We present the main estimation results of our analysis in Tables 3.2 and 3.3, and models with alternative specifications and functional forms are in Appendix Tables A3.1 - A3.10.

Before we interpret the results, we should have a note about how to interpret the coefficient estimates on hyperbolic inverse sine transformed variables for calculating elasticity of oil supply

⁸To access the spot oil price data see [EIA's spot crude oil data page](#). For futures oil prices see [EIA's crude oil NYMEX futures price page](#)

⁹To access the data see [MSCI AWCI's end of day dataset](#).

¹⁰To access the data see [FRED GS10 dataset](#).

¹¹To access the data see [FRED DTWEXBGS dataset](#).

¹²To access the data see [FRED PCOPPUSDM dataset](#).

with respect to price increases and decreases. In their simulation exercise [Bellemare and Wichman \(2020\)](#) show that for values larger than 10 in the outcome and predictor variables, the interpretation of the coefficient estimates in models involving hyperbolic inverse sine transformations to estimate elasticities is similar to that of log-log models. That is, the coefficient estimate on the predictor variable is equal to the elasticity of the outcome variable with respect to the predictor variable. Their Monte-Carlo simulations also show that for arcsinh-arcsinh specifications, the coefficient estimate of the predictor variable yields the elasticity estimate for values even above one. Following this finding, we will interpret the coefficient estimates on the hyperbolic sine transformed variable.

In [Table 3.2](#), we present the results of the OLS and fixed effects estimators. Columns with “H” indicate estimates for unconventional, horizontally drilled wells, whereas columns with “V” show estimates for conventional, vertically-drilled wells. The [Table 3.2](#) results are somewhat puzzling. While coefficient estimates for “PC Negative” ($\widehat{\beta}_{pc}$) are negative and statistically significant (implying that an oil suppliers decrease production as oil prices decline, as expected), and while it is equally encouraging to find that conventional wells appear to be less responsive to oil price changes than unconventional wells; the fact that coefficients for “PC Positive” ($\widehat{\beta}_{pc}^+$) are consistently negative and statistically significant across the four columns is problematic. For instance, results from column 1 would imply that a 1% increase in the WTI spot price of oil is associated with a 0.29% decrease in oil supply (from unconventional wells), which would run counter to economic theory. However, it should be noted that due to the autoregressive nature of the specification, a simple OLS or a regular two-way fixed effects model would be subject to bias.

In [Table 3.3](#), we present our results estimated with the Anderson-Hsaio estimator.¹³ In the first two columns we present the results of the estimation where we used second lag of the

¹³To estimate the models in this table we used Roodman’s `xtabond2` package in Stata. For details of the `xtabond2` package, see [Roodman \(2009\)](#)

dependent variable as an instrument for the first lag of oil production at month t . In the third and fourth columns we present the results of the estimation where we used the second and third lags of the dependent variable as instruments for the first lag of the outcome variable. As before, columns with “Prod-H” indicate models we ran for unconventional and horizontally drilled wells and “Prod-V” indicate models for conventional and vertically drilled wells. First, we see that the coefficient estimates for the lagged dependent variable are all under unity, indicating a dynamic stability of the panel data model structure we are using. The first column has the results for the unconventional horizontally drilled wells and the estimates are in line with the predictions of asymmetric price response hypothesis. Both coefficient estimates of the price change variables have the expected signs and statistically significant at conventional levels. The coefficient estimate for negative price change ($\widehat{\beta}_{pc}^-$) indicates that a 1% decrease in the WTI spot price of oil is associated with a 0.085% decrease in contemporaneous oil production on average. On the other hand, the coefficient estimate for positive price change ($\widehat{\beta}_{pc}^+$) indicates that a 1% increase in the WTI spot price of oil is associated with a 0.021% increase in contemporaneous oil production on average. The difference of these two coefficients is also statistically significant at 5% level (p-value of 0.0498) showing that oil supply responds asymmetrically to price increases and decreases in unconventional wells. In column 2, we see that oil supply in conventional wells does not respond to price increases or decreases, coefficient estimates of neither negative price change nor positive price change variables are statistically significant and the signs are not in expected directions. This is in line with previous literature focusing on the price elasticity of oil supply in conventional wells and suggests that oil supply does not respond to price changes. When we add the third lag of the dependent variable as an instrument to the model, we see in columns 3 and 4 that the magnitude of the coefficient estimates does not change substantially, and the signs and significance levels are the same as the

results in columns 1 and 2.

Since we used multiple lags of the dependent variable as instruments of the first lag of the dependent variable, we also checked for the instrumental variable tests. The test statistics for underidentification test and Sargan-Hansen test for overidentification tests point to the fact our models are properly identified. Also, to examine if using the second or third lags of the dependent variables are appropriate after first differencing our model for Anderson-Hsaio estimator, we ran an AR(2) test. Test results indicate that the differenced residuals do not exhibit significant AR(2) behavior. Hence, it is appropriate to use second lags as instruments for the first lag of the dependent variable.

In Appendix Tables [A3.1](#) - [A3.10](#) we also present the estimation results of OLS, two-way fixed effects and Anderson-Hsaio models in levels, logs and hyperbolic sine transformation. We see that models with OLS and two-way fixed effects estimate the coefficients of the price change variables imprecisely and with unexpected signs under different functional forms of the outcome and predictor variables. Models estimated with Anderson-Hsaio estimator with month dummies or control variables for monthly macro economic indicators are the only set of estimates that are in line with our theoretical expectations.

One concern with the estimator used in this model could be related to the proportion of zeros in our outcome variable. If we had too many zeros in our outcome variable, we could model the data-generating process explicitly and use a Tobit, zero-inflated Poisson, or negative binomial model. Our outcome variable, monthly oil production at the well-level has approximately 400,000 zeros in a panel with more than 2.7 million observations for vertical and horizontal wells. This means around 15% of our outcome variable is composed of zeros. [Bellemare and Wichman \(2020\)](#) posits that a rule of thumb could be using limited dependent variable models if the outcome variable has more

than one-third zero-valued observations. We follow this advice, and instead of using Tobit, zero-inflated Poisson, or negative binomial models, we rely on first differencing with Anderson-Hsaio estimator.

3.7 Discussion and Conclusion

In this paper, we have investigated whether asymmetries exist in oil supply responses to increases and decreases in oil prices, focusing on well-level oil production in North Dakota and distinguishing between conventional and unconventional wells. Our findings show that such asymmetries exist in the case of unconventional wells. A 1% price increase in oil prices is associated with 0.022% increase in contemporaneous oil production in unconventional wells and a 1% decrease in oil prices is associated with a 0.08% decrease in contemporaneous oil production. The difference between these two supply elasticities is also statistically significant. The fact that unconventional oil producers respond asymmetrically to oil price changes is a novel finding in the literature. As for conventional wells, consistent with emerging literature, we observe that producers do not respond to oil price changes. These findings imply that, when designing taxes/subsidies for oil production for instance, policymakers should be not only mindful of different behaviors between conventional and non-conventional oil producers, but also of different behaviors between price increases and price decreases (in the case of conventional oil producers).

We will end this paper by discussing possible extensions. First, there are three stages in the oil production process, drilling the well, starting oil production from the well, and producing oil over time. In this paper we focused on one stage, production over time. While this dimension covers an important part of decisions involved in the production process of oil, the decision to drill the well, start producing oil from it and the time between spudding a well and actual production of oil are

important aspects of oil production as well. An extension of this paper is to include asymmetries in operators' response to price in their decision to start producing oil from a spudded well. This could be easily incorporated to the analysis in this paper given the richness of monthly well-level data in North Dakota.

Second, oil and gas departments states other than North Dakota on the Williston Basin and Bakken Shale, namely Montana and Wyoming in the US and Saskatchewan in Canada provide monthly well-level data to researchers working in this area. (see Figure A3.1 for the reach of Williston Basin which encompasses Bakken shale.) A further extension of this analysis to include monthly well-level data from other states on the Bakken formation to expand the breadth of analysis.

Third, as explained in the previous sections, for both conventional and unconventional wells, the natural initial flow of oil is high due to pressure differences between the well head on the earth's surface and the oil reservoir. Therefore, controlling production by increasing or decreasing oil flow at this stage is very costly. However, after the initial phase, extra pumping is required to maintain the flow of oil. For unconventional wells, this happens at an early stage compared to the conventional wells due to the high decline in production. Hence, the decision to spud and drill the well and start production is particularly important for unconventional wells. A further extension of this study would be to examine how unconventional and conventional oil operators respond differently to spot-future price spreads in terms of the decision to drill the well after getting drilling approval and also when to start producing after drilling is completed.

3.8 Figures and Tables

3.8.1 Figures

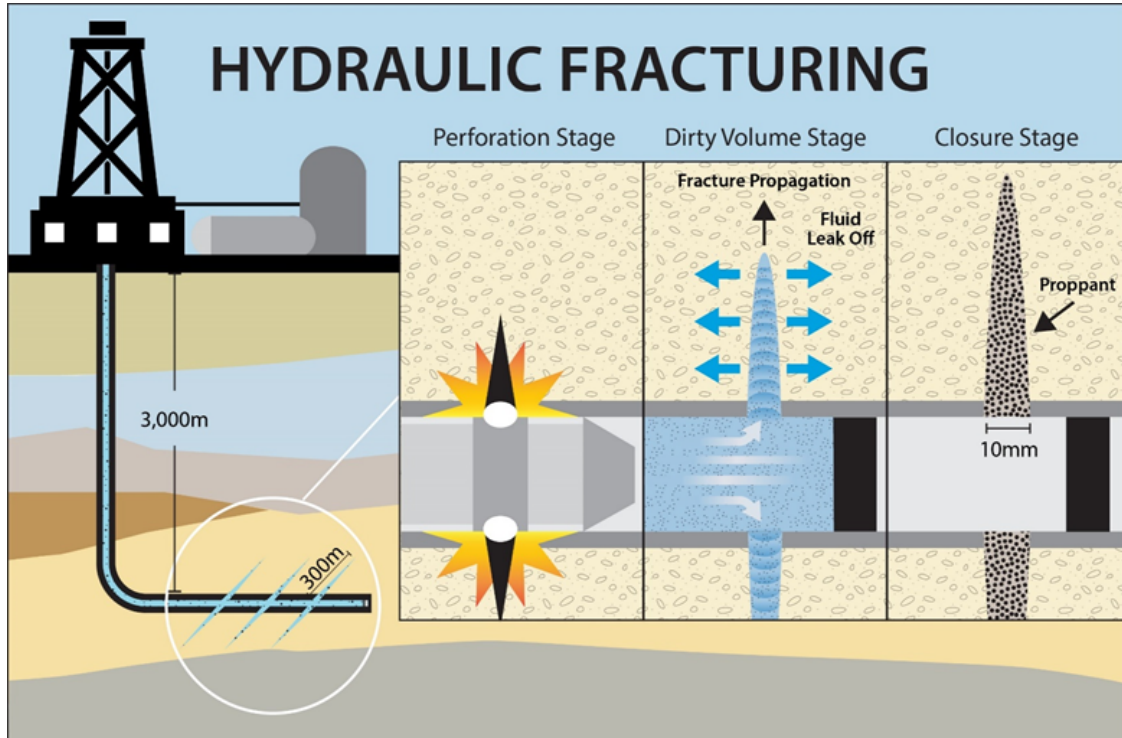


Figure 3.1: Hydraulic fracturing process.
Source: Kwon Research Group, TAMU

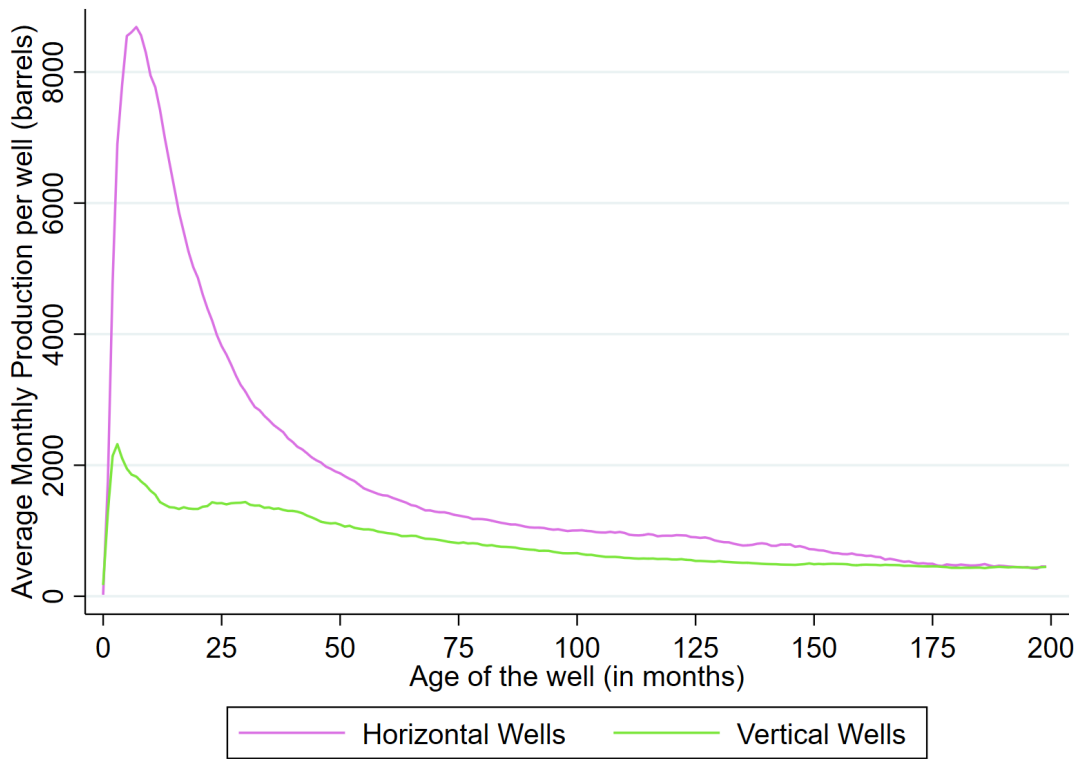


Figure 3.2: Average production after spudding in horizontal (unconventional) and vertical (conventional) wells in ND.

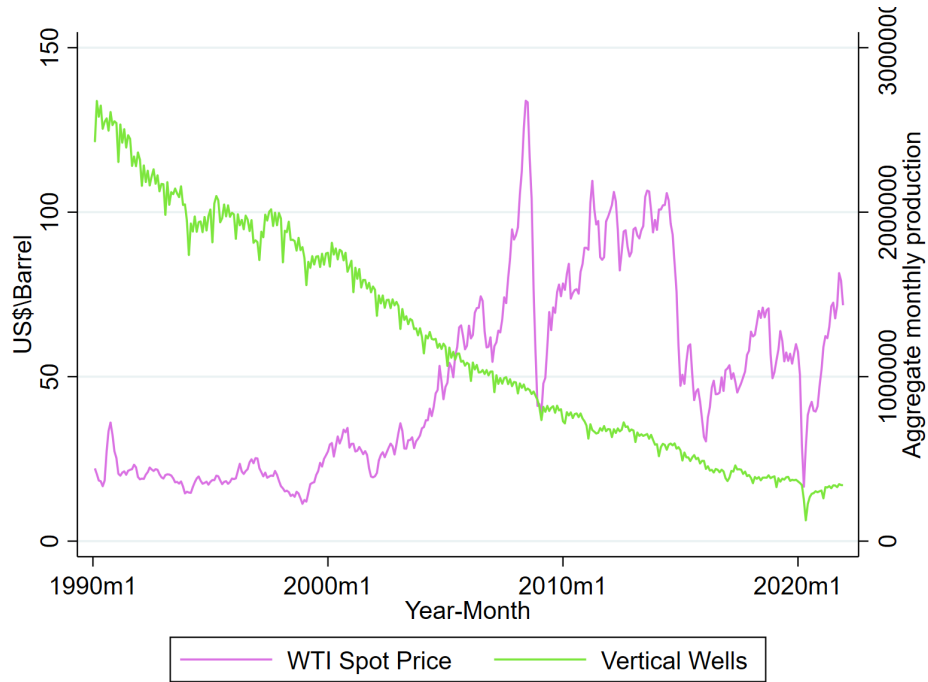


Figure 3.3: WTI spot price and aggregate monthly production in vertical wells in ND.

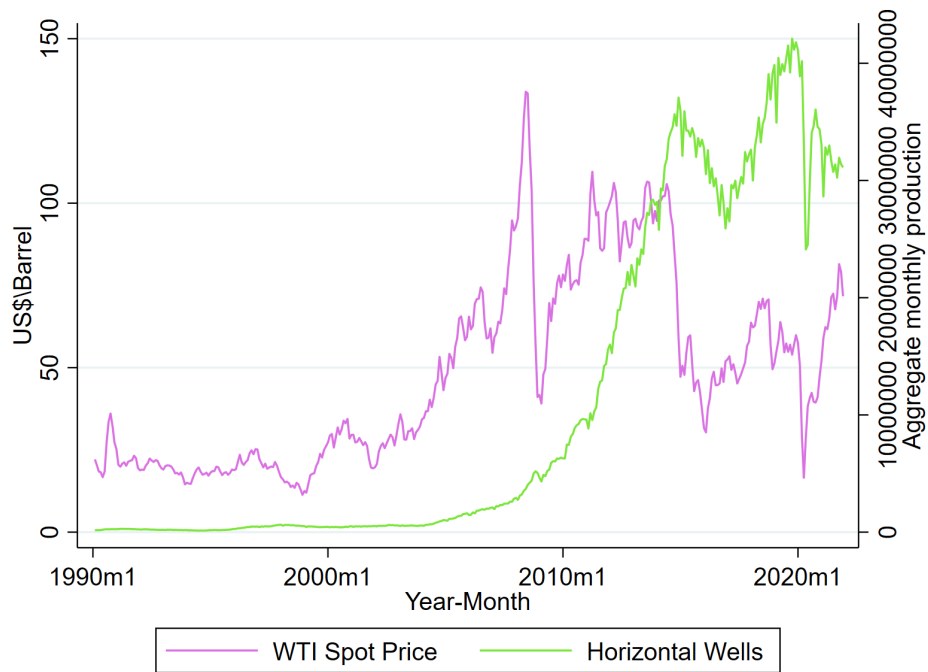


Figure 3.4: WTI spot price and aggregate monthly production in horizontal wells in ND.

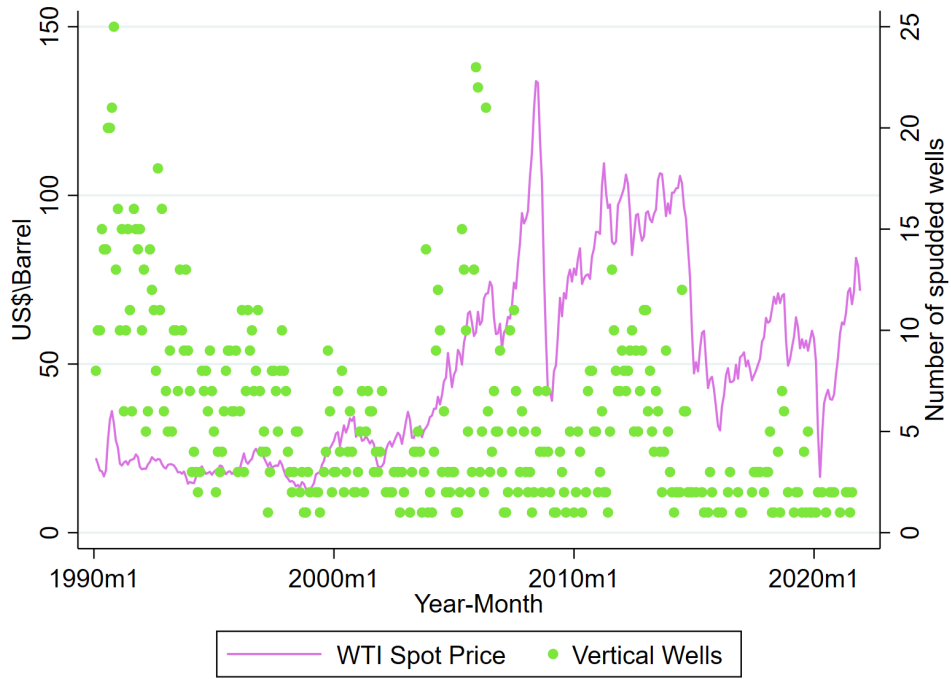


Figure 3.5: WTI spot price and number of new spudded vertical wells in ND.

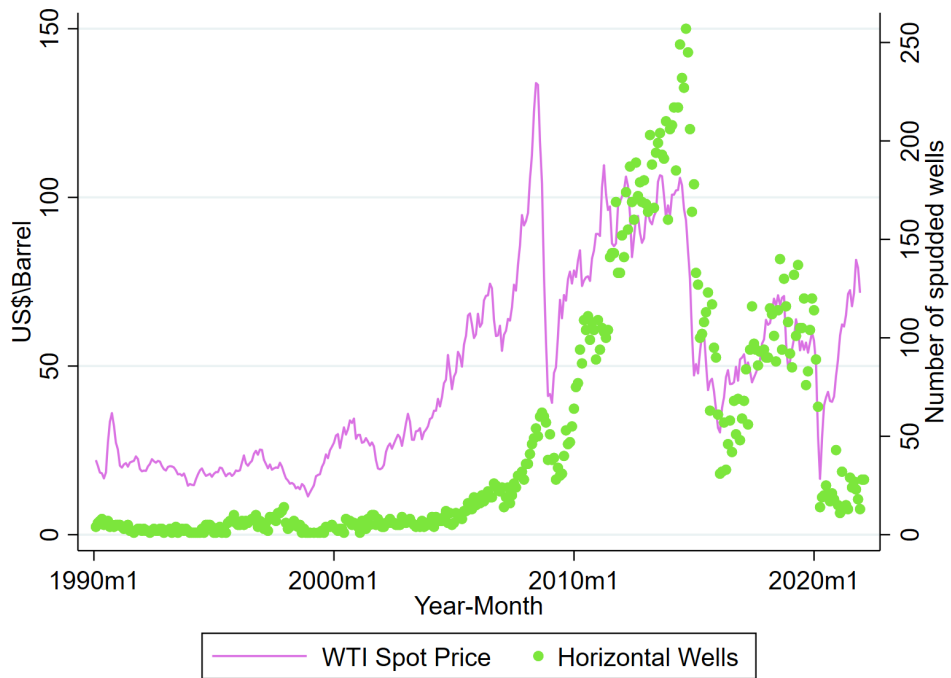


Figure 3.6: WTI spot price and number of new spudded horizontal well in ND.

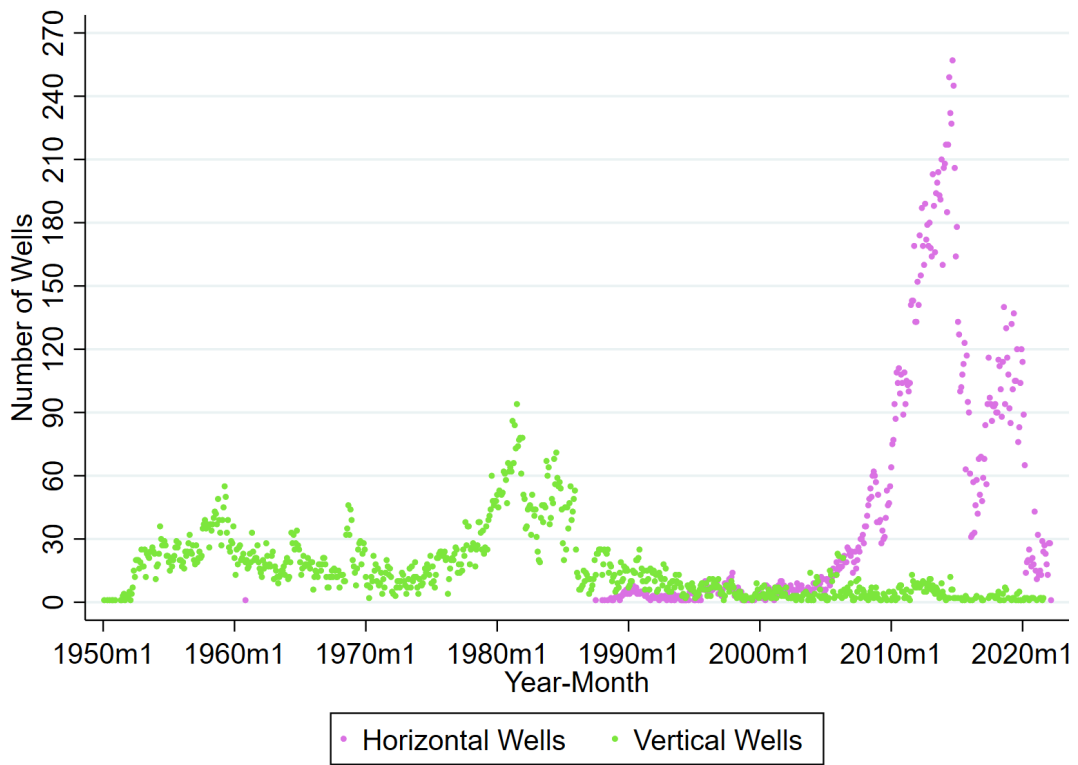


Figure 3.7: New wells spudded in each month for horizontal and vertical wellbores between 1990 and 2021.

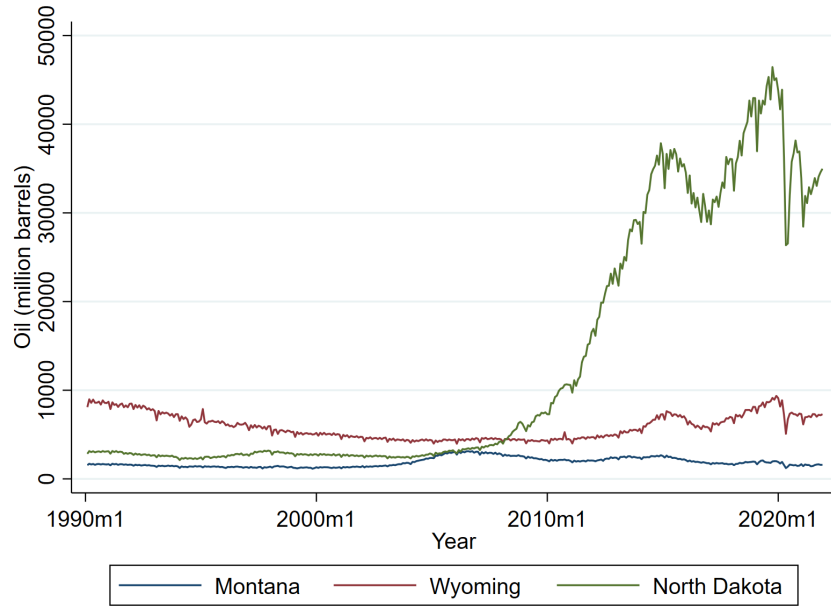


Figure 3.8: Oil production in North Dakota, Montana and Wyoming between 1990 and 2021. Source: EIA’s crude oil production by U.S. states database.

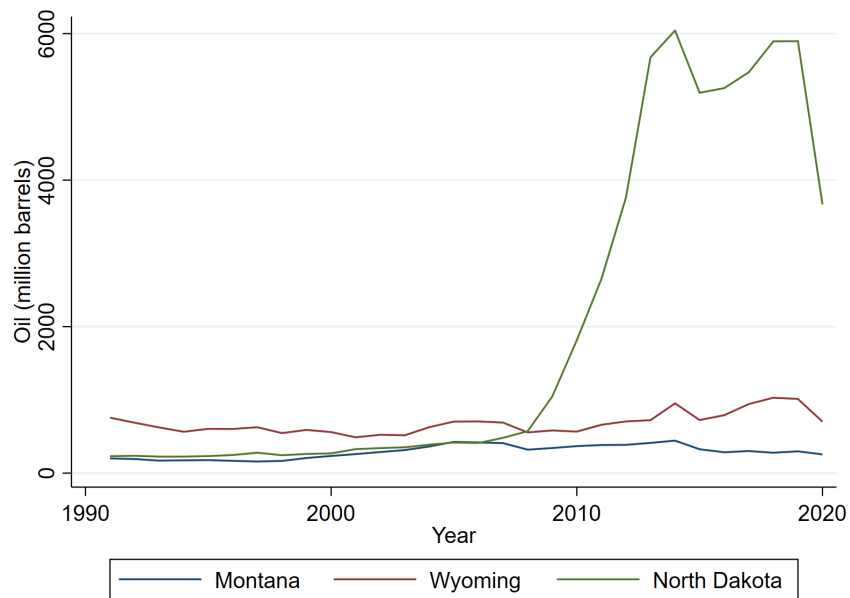


Figure 3.9: Proved oil reserves in North Dakota, Montana and Wyoming between 1990 and 2021. Source: EIA’s Crude Oil Proved Reserves, Reserves Changes, and Production by U.S. states database.

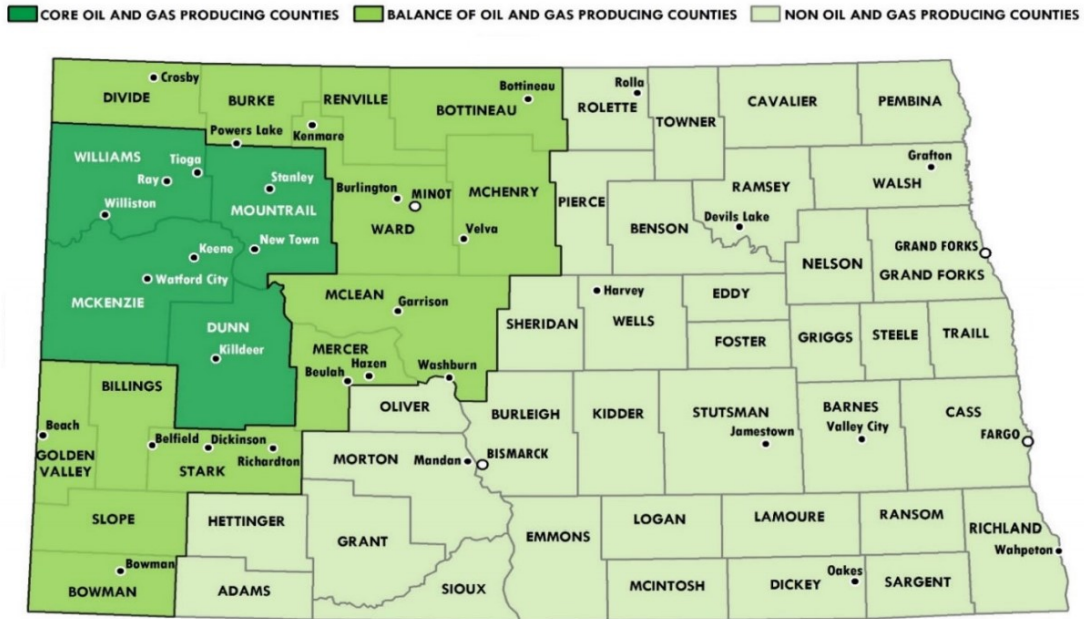


Figure 3.10: North Dakota Oil Producing Counties. Source: NDIC Oil and Gas Division.

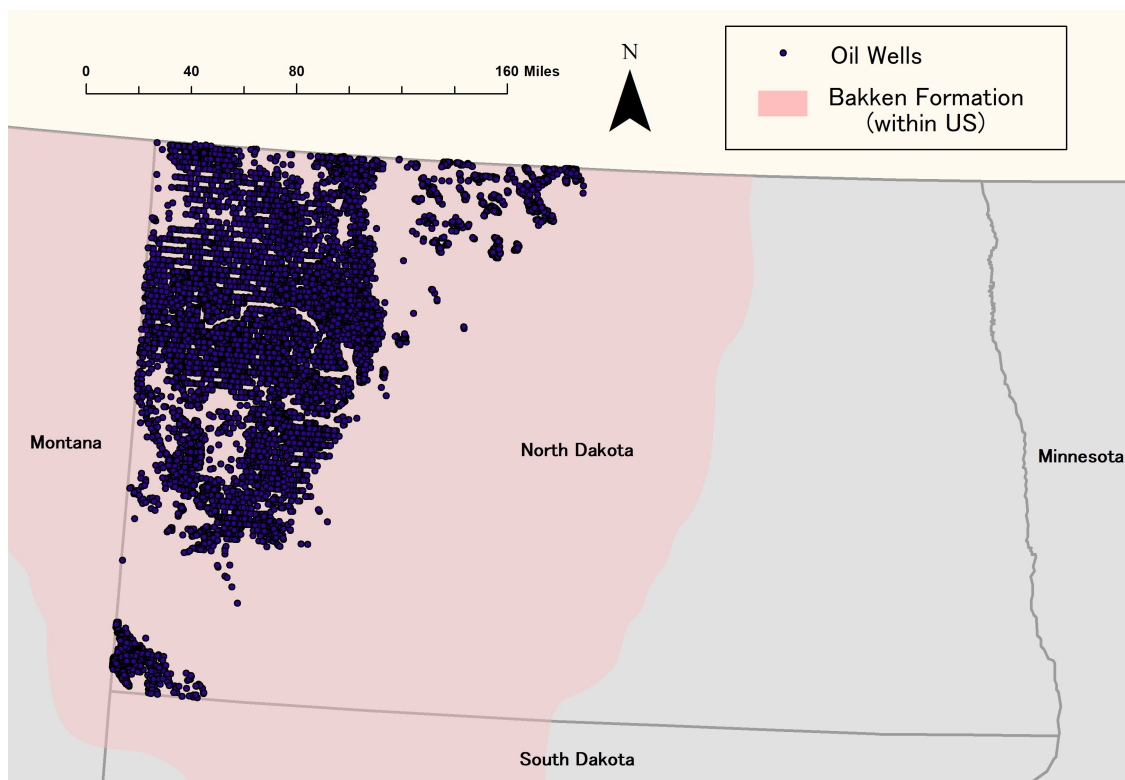


Figure 3.11: Locations of oil wells in North Dakota on Bakken Formation. Data Source: Monthly production reports (North Dakota Industrial Commission, Oil and Gas Division); 2010 US Census boundaries (ESRI). Map source: Authors' calculations.

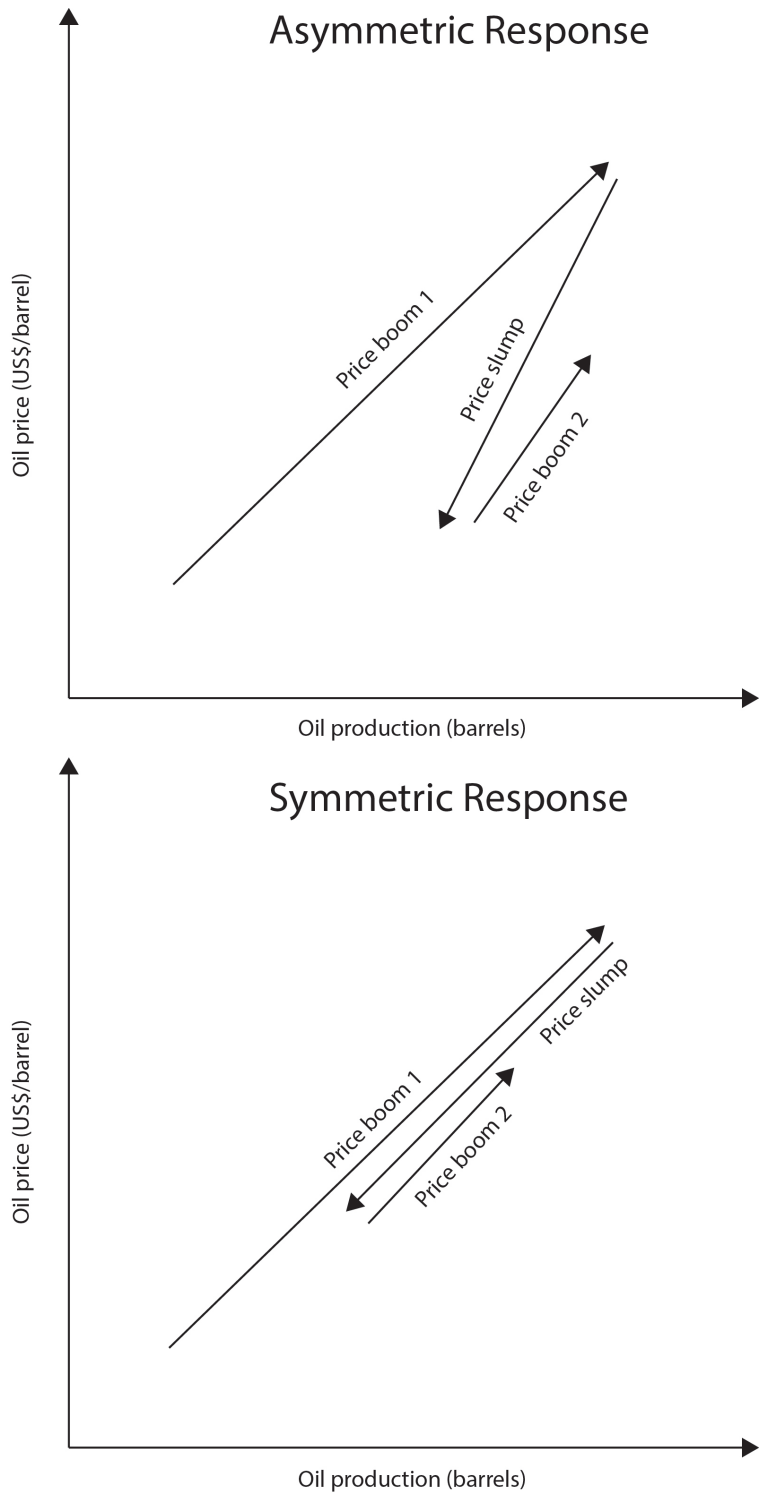


Figure 3.12: Asymmetric and symmetric supply response to oil price changes

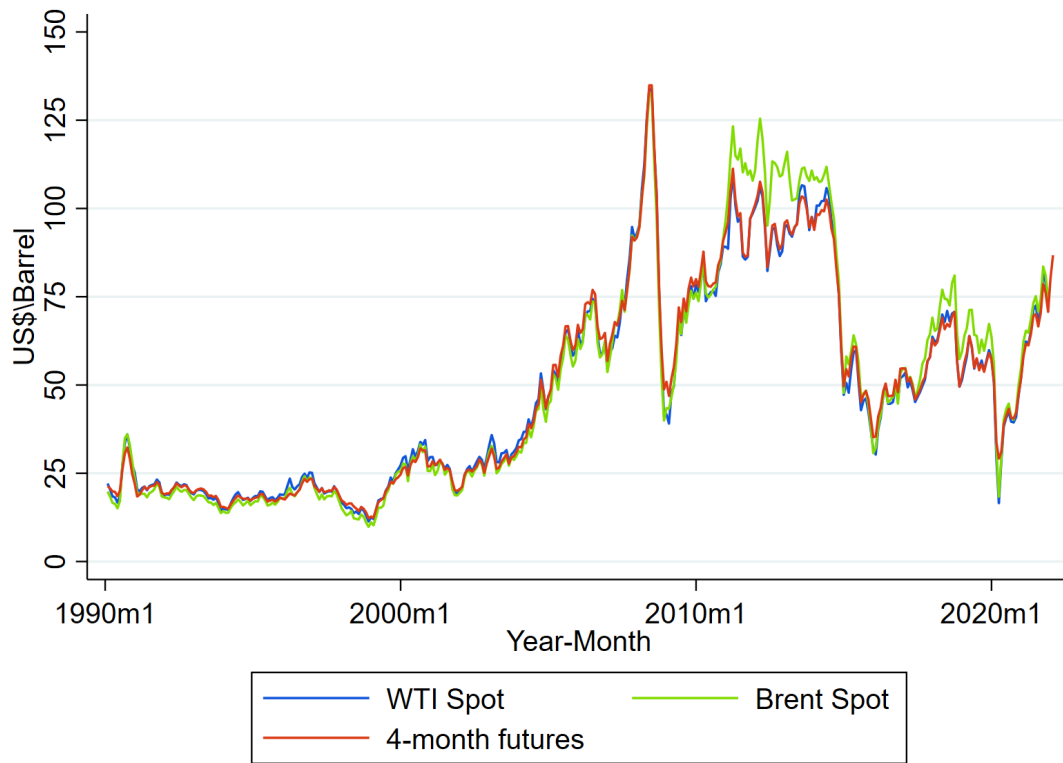


Figure 3.13: WTI spot, WTI 4-month futures and Brent spot oil prices between 1990 and 2021.

3.8.2 Tables

Table 3.1: Summary Statistics

Macro variables				
	Mean	SD	Min	Max
WTI Spot Price (\$/Barrel)	54.61	25.94	11.35	133.88
WTI 4 month futures (\$/Barrel)	55.03	25.69	12.23	134.89
Negative price change (\$/Barrel)	1.85	3.68	0.00	27.50
Positive price change (\$/Barrel)	1.88	2.66	0.00	14.28
US 10 Year Treasury Yield	3.23	1.92	0.62	8.89
MSCI Index (AWCI)	395.5	155.3	104.3	754.8
USD Index	87.79	8.23	69.06	112.17
Copper Price (\$/Tonne)	5,545	2,344	1,377	10,166

Well-level variables	
	Count
Observations (All)	2,856,749
Observations (Horizontal)	1,644,904
Observations (Vertical)	1,074,359
Number of wells (All)	23,351
Number of wells (Horizontal)	17,699
Number of wells (Vertical)	4,926

	Mean	SD	Max
Monthly oil production (Barrels) (All)	1,682.8	3,418.5	139,068
Monthly oil production (Barrels) (Horizontal)	2,560.7	4,106	139,068
Monthly oil production (Barrels) (Vertical)	430.6	1,274.9	92,094

Table 3.2: OLS and FE Models with IHS

VARIABLES	(1) OLS - H	(2) OLS - V	(3) FE - H	(4) FE - V
Production (t-1)	0.7064*** (0.0019)	0.7086*** (0.0055)	0.6321*** (0.0020)	0.6697*** (0.0057)
Production (t-2)	0.1033*** (0.0019)	0.2413*** (0.0054)	0.0453*** (0.0017)	0.2037*** (0.0054)
PC Negative	-0.3603*** (0.0670)	-0.1135*** (0.0193)	-2.0238*** (0.1182)	-0.4140*** (0.0199)
PC Positive	-0.2883*** (0.0605)	-0.0946*** (0.0137)	-1.7965*** (0.1072)	-0.3722*** (0.0147)
Constant	2.2495*** (0.1811)	0.4837*** (0.0343)	7.3964*** (0.3204)	1.4585*** (0.0381)
Observations	1,608,958	1,065,735	1,608,958	1,065,735
R-squared	0.6512	0.8831	0.5471	0.7833
Well FE	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes
Macro Controls	Yes	No	No	No

Dependent variable is the hyperbolic sine transformed monthly oil production in barrels.

Robust standard errors clustered at the well and month level in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

Table 3.3: FD Models with IHS

VARIABLES	(1) Prod - H	(2) Prod - V	(3) Prod - H	(4) Prod - V
Production (t-1)	0.6056*** (0.0100)	0.2455*** (0.0282)	0.5554*** (0.0061)	0.3056*** (0.0170)
PC Negative	-0.0842*** (0.0239)	-0.0724 (0.0480)	-0.0804*** (0.0233)	-0.0741 (0.0494)
PC Positive	0.0205** (0.0104)	-0.0313 (0.0226)	0.0222** (0.0102)	-0.0313 (0.0236)
Constant	0.0844*** (0.0169)	0.0603* (0.0354)	0.0801*** (0.0165)	0.0593 (0.0362)
Observations	1,591,175	1,060,184	1,573,466	1,054,730
Number of Wells	17,552	4,679	17,497	4,662
Month FE	Yes	Yes	Yes	Yes
Prod (t-2) IV	Yes	Yes	Yes	Yes
Prod (t-3) IV	No	No	Yes	Yes
<i>Hypothesis Test</i>				
$H_0 : \beta_{pc}^+ + \beta_{pc}^- \geq 0$				
$H_1 : \beta_{pc}^+ + \beta_{pc}^- < 0$				
<i>P - value</i>	0.0402		0.0485	

Dependent variable is the hyperbolic sine transformed monthly oil production in barrels.

Robust standard errors clustered at the well and month level in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

Chapter 4

YELLOW VESTS AND GREEN TAXES: EQUITY MARKET RESPONSE TO THE FRENCH CARBON TAX

4.1 Introduction

After years of planning and numerous proposals by different committees and legislators, the French carbon tax was put into effect in 2014. In the following years, the policy became the largest carbon tax program in terms of government revenue ([The World Bank 2019:7](#)) and France now has one of the highest tax rates per ton of CO₂ in the world ([The World Bank 2021](#)). Despite the initial ambitious targets to increase the tax rate from EUR7/tCO₂e in 2014 to EUR86.2/tCO₂e by 2022, the regressive nature of the tax created a backlash among populations heavily impacted by it ([Berry 2019](#)). As a result, the Yellow Vests protest that started in November 2018 in response to rising gasoline prices, quickly became a massive public movement. A month later, the protests caused the French government to suspend its plans to increase the French carbon tax rate, on December 4, 2018. The unexpected nature of this decision makes it a suitable “event” to assess how shifts in the expected stringency of environmental and climate policies affect corporate performance.

In this paper, I analyze the impact of the unexpected change in the trajectory of the French carbon tax on corporate performance proxied by firms’ stock market performance. I particularly focus on the excess returns on equities of French manufacturing sectors with varying degrees of energy intensity immediately after the announcement for the suspension of the rate increase. The research question I aim to answer in this paper is, does the market reward or punish manufacturing

firms according to their energy intensity in response to the relaxation of environmental regulations. While the answer to this question might appear obvious, the peculiar aspect of the French context is that the French carbon tax is not primarily levied on the energy or fuel expenses of manufacturing sectors. Instead, it is levied on transport and heating fuels and end users of these fuels (i.e., households) bear the majority of the tax burden. Hence, I aim to understand if the changes in expectations about the future of climate and environmental regulations and decarbonization efforts alter market responses to the valuation of firms with respect to their energy intensity.

To answer the research question, I conduct an event study to estimate the abnormal or excess returns of each manufacturing sector with a sufficient number of firms traded in the Euronext Paris stock exchange. I estimate the CAPM-adjusted average and cumulative abnormal returns at the sectoral level with single index and multi-factor models under varying event-window ranges. Results indicate that sectors with high energy intensity, such as non-metal minerals, basic metals and chemicals, benefited from the announcement of the carbon tax rate increase suspension and had positive excess returns. On the other hand, manufacturing sectors with lower energy intensity, such as pharmaceuticals and electronics, were adversely affected by the announcement and had negative excess returns. The results are robust to longer event windows, indicating investors did not over or under-react to the announcement, and equity returns did not exhibit mean reversion after the event.

The main contribution of this paper is the causal link it forms between an environmental policy change and corporate performance. Environmental regulations and climate policies take a long time to plan and implement, and major changes to them occur after lengthy deliberations. Hence, it is hard to quantify the impact of the shifts in these policies in a causal way especially in unitary (non-federal) states. Focusing on the unexpected change in the implementation of a major carbon

tax policy which has repercussions on the broader climate policy expectations of a jurisdiction, this analysis causally identifies the impact of shifting expectations on environmental regulation stringency on corporate performance.

In terms of policy implications, the findings of the paper point to a similar outcome presented in other works of the literature on the effects of corporate performance and environmental regulations. Investors are highly sensitive to shifts in environmental and climate policy and they adjust their expectations and update their priors about corporate performance in line with the efficient market hypothesis.

The paper is organized as follows: Section 4.2 provides an overview of the literature on the impacts of environmental regulation on corporate performance and methods to estimate this relationship. Section 4.3 gives background information on the French carbon tax and the Yellow Vests protests. Sections 4.4 and 4.5 introduce the empirical methods and data used to answer the research question for this project, and Section 4.6 presents the findings. The paper concludes with a discussion about policy implications and suggestions on future research in Section 4.7.

4.2 Literature Review

A central dimension of the debate on the environmental and specifically climate regulation is about the economic and financial impacts. Numerous researchers explored the corporate performance in response to changes in environmental regulations and standards by examining stock returns, profits, employment and output at the firm-level. While recent studies indicate that environmental and climate regulations do not have an adverse negative effect on corporate performance, the debate is still inconclusive. Those who oppose environmental regulations point out to potential negative impact on the economy due to rising costs of production, decreasing employment and profits and

overall deterioration of corporate financial indicators (Ramiah et al. 2013). In contrast to this view, other researchers argue that the potential adverse effects of environmental regulation are overblown, and the empirical findings do not corroborate with opponents' views both at the firm and macro-level outcomes (Moosa and Ramiah 2014).

A popular way to measure the impact of regulation on corporate performance is proxying corporate performance with stock market returns. This approach is a widely studied and used since the inception event studies following works of Fama et al. (1969) and Brown and Warner (1985). For instance, works by Schwert (1981), Binder (1985) and Teets (1992) focused on the impact of regulation on the U.S. stock market. Outside of the U.S., Antoniou and Pescetto (1997) examined the effects of regulatory announcements about competition pricing on British telecom's cost of equity capital, while Robinson and Taylor (1998)'s focus was on the effect of regulation on the U.K.'s electricity distribution firms.

As a subset of the literature, the effects of environmental regulation on firms' stock market performance received particular interest as well. Sawkins (1996) and Pescetto (2008) investigated the effect of regulatory actions in competition, pricing policy and the quality of service in the water industry on the equity performance of English and Welsh water utilities. In more recent research, Ramiah et al. (2013)'s analysis focuses on the impact of environmental regulation announcements, particularly the carbon pollution reduction scheme (CPRS) on equity performance in Australian stock market. Ramiah et al. (2015)'s work on the corporate performance of Chinese firms as proxied by stock returns in response to environmental policy announcements finds inconclusive results due to lack of enforcement and pro-growth political and social environment. Ramelli et al. (2021) examine the effect of Donald Trump's presidential election and Scott Pruitt's ensuing nomination for EPA administrator on the performance of carbon-intensive firms' equity returns.

For Europe, [Bushnell et al. \(2013\)](#) estimate the impact of a rapid decrease in EU ETS allowance prices on equity prices of firms publicly traded on the EUROSTOXX index.¹ They conduct an event study for the period of the price drop and found that prices for carbon and electricity intensive firms decreased as a result of the reduction in price of products these firms sell and firms' profit margins. [Pham et al. \(2020\)](#) assess the impact of environmental regulations on the French stock market, particularly regulations on the EU ETS, air, soil and water. Their findings indicate that the French stock market is sensitive to environmental regulations pertaining to GHG emissions while reactions to other environmental regulations are negligible. The tightening of the EU ETS regulations in the last decade created negative stock market reactions in chemicals, oil and gas industries while other polluters not covered under the EU ETS such as construction and industrial transportation produced positive returns.

Estimating the impact of carbon pricing initiatives on macro-economic indicators has also been a subject of various studies in the environmental regulatory impact literature. [Azevedo et al. \(2018\)](#) and [Metcalf \(2019\)](#) estimate the effect of British Columbia's revenue neutral carbon tax policy on economic growth and employment. Also [Metcalf and Stock \(2020\)](#) find that carbon tax policies in Europe do not lead to a decrease in GDP growth or increase in unemployment rates. [Dechezleprêtre et al. \(2018\)](#)'s work focuses on the impact of the EU ETS on the GHG emissions and economic performance of regulated firms. They don't find any negative impact on economic performance of firms in France, Netherlands, Norway and the U.K. in terms of revenues, assets, profits and employment. [Dussaux \(2020\)](#)'s analysis estimates the effect of energy prices and carbon taxation on French firms' environmental and economic performance. He finds that the increase in

¹EUROSTOXX index is a stock index for equities traded in eleven Eurozone countries, Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. It covers 95% of market capitalization in the Eurozone.

energy prices does not lead to any significant effects on net employment while decreasing the CO₂ emissions in the manufacturing sector.

Given this background, the main contribution of this paper is its focus on a significant carbon tax policy and the unexpected change in its implementation which also has repercussions on the broader climate policy expectations of an industrialized country with a developed equity market. Previous papers focusing on industrialized countries examine events or regulations that were already in the making before the policy announcement events took place. In this regard, this paper's identification strategy is closest to the work by [Ramelli et al. \(2021\)](#). These authors use the unexpected Donald Trump's election as the U.S. president as an event that led to diverging volatility in equities of firms that are climate conscious and those that are not.

An additional contribution of this study is in the broader carbon taxation literature. Planning and implementation of carbon tax policies take a long time to materialize and usually when policies attached to them are changed, they occur after extended legislative processes. So, these changes are not unexpected events and it is a challenging task to quantitatively estimate the firm-level impacts of carbon tax policy changes within unitary states. This paper uses a unique, unexpected event about the implementation of the largest carbon tax policy in existence that did not require a legislative process and the findings shed light on sectoral-level effects of an expected change in the price of carbon.

4.3 Background information

4.3.1 The French carbon tax

The French carbon tax policy was proposed under different French governments but could not be enacted after rounds of consultations and amendments. The French government led by Francois Hollande, relying on the work carried out previously by the Grenelle I and II processes ² ended in 2009 and recommendations from the Committee for Ecological Taxation in 2013, enacted the French carbon tax in 2014 following the approval of the 2014 Finance Bill in December 2013. The tax was initiated with a rate of EUR7/tCO_{2e} and applied in line with the carbon content of the fossil fuels it covers. The carbon tax policy had a clear rate increase trajectory that reached EUR44.6/tCO_{2e} in 2018 and was supposed to continue increasing to EUR86.2/tCO_{2e} by 2022. The planned trajectory can be seen in the red connected line in Figure 4.1. Following the “Yellow Vests” protests, which is detailed in the next section, the French government led by Emmanuel Macron announced unexpectedly on December 4, 2018 the six month suspension of the planned increase for 2019 carbon tax rates (Thomson Reuters 2018, Willsher 2018). The increase then suspended indefinitely by the government and the current rate stands frozen at EUR44.6/tCO_{2e} since 2018 (see blue connected line in Figure 4.1).

The carbon tax is integrated into the existing domestic taxes on energy consumption named TIC. ³ French law makers did not opt for creating a new fiscal instrument for taxing carbon content of fossil fuels to lower administrative costs and ease of implementation under TIC (Sénat 2009). Consequently, it was officially named as “carbon component” (*composante carbone* in French) of

²For details of the Grenelle I and II, see [Loi No 2009-967 du 3 août 2009](#).

³Domestic Tax on Consumption, *Taxes Intérieures de Consommation* in French

the energy taxes. TIC is composed of three components: TICPE⁴ on consumption of petroleum products, TICGN⁵ on natural gas consumption and TICC⁶ on coal consumption. As it is part of the energy consumption taxes, it is an excise tax collected downstream. The last purchasers or consumers pay the tax.

The French carbon tax covers transport fuels (gas and diesel) and heating fuels (natural gas, coal and fuel-oil) and aims to reduce GHG emissions from transport and building sectors. Emissions from the agricultural sector are partially exempt. There is no overlap between the EU ETS and the French carbon tax in terms of fuel and sectoral coverage as the tax primarily aims to cover sectors not covered under the EU ETS. The EU ETS covers emissions from manufacturing sectors, electricity generation in installations above 20MW capacity and aviation. There are more than 15,000 installations covered under the EU ETS and approximately 1,000 of these installations are located in France, mostly in the manufacturing sector (The European Union 2022). As a result, most of the industrial emissions and all of the emissions from the electricity generation are exempt from the French carbon tax to avoid double taxation.⁷ Only 8% of the industrial emissions are covered under the carbon tax (Callonnec et al. 2019) and a full exemption applies to air and maritime transport along with a full refund for public transport and heavy trucks weighing over 7.5 metric tons. Under the scope of this paper, these exemptions and the lack of overlap with the EU ETS indicates that the public traded firms are not directly impacted by the French carbon tax in terms of operating costs but they might be impacted via sales and profits.

⁴Domestic Tax on Consumption of Energy Products, *Taxe Intérieure de Consommation sur les Produits Énergétiques* in French.

⁵Domestic Tax on Consumption of Natural Gas, *Taxe Intérieure de Consommation sur le Gaz Naturel* in French.

⁶Domestic Tax on Consumption of Coal *Taxe Intérieure de Consommation sur le Charbon* in French.

⁷It should also be noted that France has a relatively clean electricity grid and even if it was taxed under the French carbon tax like under Finland carbon tax, it would have a negligible effect on electricity prices. Approximately 60% of the installed capacity in France comes from nuclear energy, 25% from hydropower, 16% from wind energy and 11% from other renewable sources (IAEA 2020)

Despite these exemptions and narrow application to transport and heating fuels, the French carbon tax generates the highest revenue among all carbon pricing instruments worldwide (Postic and Fetet 2021, The World Bank 2019).⁸ The current rate of EUR44.6/tCO₂e is also one of the highest tax rates among all carbon taxes worldwide. As of 2021 the French carbon tax generated more than 8 billion Euros which is approximately four times more than Sweden carbon tax, the second highest revenue generating CPI in Europe (The World Bank 2021). However, the policy makers did not consider recycling these revenues back to the taxpayers. Instead, funneled these funds to finance a tax credit for competitiveness and employment and a value added tax reduction for improving energy efficiency in buildings (Rogissart et al. 2018). Instead of revenue recycling in the form of carbon dividends, these policy choices by the policy makers led to the discontent of citizens directly impacted by the transport and heating fuel price increases and spurred the Yellow Vests protests, which I turn to in the next section.

4.3.2 Yellow Vest Protests

The French carbon tax is mainly paid by households which comprise the majority of end users of transport and heating fuels. Households paid approximately EUR5.2 billion for the French carbon tax in 2019 which was 58% of the total French carbon tax revenue in 2019 (Callonnec et al. 2019). Berry (2019) focuses on the regressive nature of fuel tax increases due to the French carbon tax. Her findings point to the fact that French carbon tax, without revenue recycling to households, increased fuel poverty and low-income households bear the highest burden of this policy. The impact of the carbon tax on the poorest 10% is 2.7 times greater than on the wealthiest 10% (Berry 2019:89).

⁸Other carbon taxes in Europe such as Finland and Norway carbon tax generate higher per capita revenue when compared to the French carbon tax.

From 2017 to 2018, the rate of carbon tax increased by almost 50%, from EUR30.5/tCO_{2e} to EUR44.6/tCO_{2e}.⁹ Accompanying the rate hike, global oil prices rose sharply from mid-2017 to 2018.¹⁰ Therefore, gasoline and oil prices spiked and commuters reliant on their motor vehicles in rural areas and countryside were negatively impacted in terms of their fuel expenses (Hanafi et al. 2019). The adverse effects of gas and diesel price hikes also coincided with negative opinions about the Macron government's decision to abolish wealth tax (Solidarity tax on wealth, *L'impôt de solidarité sur la fortune (ISF)*) for individual assets over EUR1.3million in January 2018.

With this background, the protests started after the viral video of a protester named Jacline Mouraud opposing the rising fuel prices was posted on Facebook in October 18, 2018. On October 24, the “*gilets jaunes*” (a yellow high-visibility vest) was proposed as the rallying sign of the movement and quickly became the symbol of resistance against the carbon tax (Boyer et al. 2020). During the first part of the protests, the peak of the mobilization was on November 17, when motor blockades started with around 300,000 protesters participating. The following day, the French Prime Minister Eduard Philippe announced that the government would not back down on proposed fuel tax increases due to the upcoming carbon tax rate increase (France 24 2018a). In the second phase of the protests, the civil unrest which started with motor blockades in mid-November, turned into an urban guerilla warfare and on December 1, 2018 violent clashes erupted between protesters and the security forces at the roundabout around the Arc de Triomphe in Paris (France 24 2018b). Finally, in the face of escalating protests, the government announced that it would suspend the carbon tax rate increase for six-months on December 4, 2018 (Carbon Pulse 2018). The timeline of the events leading to the suspension of the carbon tax increase are listed in Table 4.1.

⁹See Figure 4.1 for the graphical representation of the slope increase before and after 2017.

¹⁰The price of Brent crude almost doubled and increased from less than \$50/bbl in June 2016 to more than \$80/bbl in June 2017.

The Google search trends, which show interest in words frequently searched over time also give us a snapshot of the evolution of the events through words that are directly related to the protests.

¹¹ In Figure 4.2, the search trends for Yellow Vests (*Gilets Jaunes*), carbon tax (*taxe carbone*), cancellation of carbon tax (*suppression de taxe carbone*) and domestic tax on energy products (*TICPE*) are presented. The values on the vertical axis represent search interest relative to the highest point on the chart for France where a value of 100 is the peak popularity for the term. We see that words *Gilets Jaunes*, *taxe carbone* and *TICPE* rose in search popularity as protests gained momentum and reached maximum popularity around the decision to suspend carbon tax rate increases. Their popularity dwindled following the announcement. The word bundle for the cancellation of carbon tax drew a brief and sudden interest on the day of the announcement, underlining the unexpected nature of the decision.

The public backlash against the carbon tax rate rise pointed to the fact that those who initiated the carbon tax policy did not take into account the redistributive effects. They particularly failed to account for the negative impacts of the carbon tax on suburban populations who have no choice other than relying on their automobiles for their daily lives which makes their demand for gasoline or diesel inelastic (Aghion et al. 2021:308-309). Following the protests, Douenne and Fabre (2022)'s survey analysis showed that the protesters even rejected a "citizens' dividend" attached to the carbon tax policy and they overestimated their monetary losses and the regressivity of the tax policy. Nonetheless, after the government backed down on carbon tax rates, a positive outcome of the protests was the decentralization of the climate action in France. In the months succeeding the protests, the government initiated the "Citizens' Convention for the Climate" gathering randomly selected 150 citizens to formulate proposals to fight climate change and achieve France's goal of

¹¹To access Google search trends, see: <https://trends.google.com/>.

reducing GHG emissions up to 40% by 2030. ¹²

While blockades to protest government policies are quite common in France, the synchronous nature of protests in different urban and rural areas, the rapid increase of violent clashes between security forces and the growth in the scale of protests were unprecedented. Also, while the government wanted to stand firm to protect the climate change legislation, it took them less than two weeks to concede to protesters' demands and suspend the planned increase in the carbon tax rise for 2019. President Macron even announced further concessions in the form of tax reform on December 10, 2018. The empirical strategy in this paper rests on this unexpected nature of both the Yellow Vest protests and the announcement of the tax increase suspension.

4.4 Empirical Strategy

Establishing a causal link between a carbon tax policy change and firm-level outcomes in a unitary (non-federal) state like France could be problematic due to endogeneity concerns. However, unexpected policy announcements creating variation at firm-level outcomes and particularly firm valuations through stock prices might allow for causal identification. Event studies that use equity price responses to specific events provide a convenient way to identify relationships between environmental policy change and firm valuations (Schwert 1981). Also, using event studies to measure tax incidence through asset prices is a widely used method (Cutler 1988, MacKinlay 1997). I exploit the unexpected change in the carbon tax rate in France, which occurred on December 4, 2018, as a source of an exogenous change in the expectations about French environmental policy. As explained in Section 4.3.1, the ambitious decarbonization efforts in France, especially in sectors not covered by the EU ETS, are hampered with this policy reversal. The presumably exogenous kink

¹²For details of the Convention, see: <https://www.conventioncitoyennepourleclimat.fr/>

in the trajectory of the carbon tax rate in France, as displayed in Figure 4.1 creates an opportunity to assess how the stock market and firm valuations respond to changes in environmental policy.

In this analysis, first, I focus on two sets of returns, (1) the *ex post* abnormal or excess returns (*AR*) at the manufacturing sector-level calculated with the capital asset pricing model (CAPM), controlling for the returns in the Euronext Paris Index and the risk-free rate set by the European Central Bank, and (2) the *ex post* abnormal returns with respect to Fama-French three factor model. Then, I aggregate these two sets of abnormal returns at the manufacturing sector level to generate the average abnormal returns *AAR* for each sector. According to the efficient market hypothesis (EMH), investors react to new information immediately and prices reflect the information content of the underlying event instantly. Yet, when EMH does not hold, the initial response of investors may be an over or under-reaction (Pham et al. 2020). To discriminate if the stock market exhibits mean reversion or continues to deviate from the mean price, I estimate the cumulative average abnormal return (*CAAR*) for each sector in multiple day event windows with 3, 5, and 10 days ranges before and after the French carbon tax announcement.

To determine the statistical significance of *CAARs*, I test for the null hypothesis that a *CAAR* of a specific sector is equal to zero ($H_0 : E(CAAR_s) = 0$) with a t-test, as none of the sectors in our panel have more than 30 firms. If the abnormal returns for a particular firm is positive, we can understand that the investors believe profits of these firms will increase in the period succeeding the event, even though the French carbon tax is not directly applicable as a cost factor to the manufacturing firms traded in Euronext Paris. For energy intensive firms, if investors expect a more lenient environmental and climate regulation in France following the event, *CAARs* for these sectors should be positive. On the other hand, less energy-intensive firms that benefit from strict environmental regulation would be impacted adversely in the period following the event and their

CAARs should be negative.

To generate *CAARs* under the two models described above, I follow the steps below. First, by using a single index, we can model the CAPM-adjusted returns for each individual equity's return with the equation:

$$R_{ist} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \epsilon_{ist} \quad (4.1)$$

where R_{ist} is the return for firm i in sector s on day t as daily percentage change in its stock price, R_{mt} is the return on the Euronext Paris index on day t as daily percentage change and R_{ft} is the risk-free rate for which I use the one-day inter-bank interest rate in the Eurozone. The difference between the R_{mt} and R_{ft} is the excess return on the Euronext Paris Index.

Abnormal or excess returns is equivalent to the error term in the equation above and is defined in the equation below if we use the single index model:

$$AR_{ist} = (R_{ist} - R_{ft}) - (\hat{\alpha}_i + \hat{\beta}_i(R_{mt} - R_{ft})) \quad (4.2)$$

where AR_{ist} is the abnormal or excess return for each firm i in sector s on day t as daily percentage change in its stock price. Other terms are the same as in equation 4.1.

As indicated above, I also use a multifactor model (MFM), particularly the three-factor model introduced by [Fama and French \(1993\)](#) which introduces two more factors to the model in equation 4.2, the size of firms and book-to-market values. The three factors used in this model are small minus big (SMB), high minus low (HML), and the portfolio's return less the risk-free rate of return but we already include the third factor in equation 4.2 with the CAPM adjustment. SMB accounts for publicly traded companies with small market caps that generate higher returns, while HML accounts for value stocks with high book-to-market ratios that generate higher returns in

comparison to the market (Kothari and Werner 2008). The model to estimate the MFM model is in the equation below:

$$R_{ist} - R_{ft} = \alpha_i + \beta_{1i}(R_{mt} - R_{ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \epsilon_{ist} \quad (4.3)$$

where R_{ist} , R_{ft} and R_{mt} are the same as in equation 4.1, SMB_t and HML_t are the small minus big and high minus low are from the European markets. In the ideal case I should be using these two factors from the French equity markets but Kenneth French's database does not provide this data and I opt for the second best option to use the three factors for the European equity markets.

For the MFM, to calculate the abnormal returns for each equity, we can use the method in equation 4.2, and equation 4.3 can be rearranged as:

$$AR_{ist} = (R_{ist} - R_{ft}) - (\widehat{\alpha}_i + \widehat{\beta}_{1i}(R_{mt} - R_{ft}) + \widehat{\beta}_{2i}SMB_t + \widehat{\beta}_{3i}HML_t) \quad (4.4)$$

To check the efficient market hypothesis, I am using event windows with varying lengths. For event windows longer than one and spanning multiple days I aggregate the returns in this event window and generate cumulative abnormal returns (CAR) for each firm i in sector s by:

$$CAR_{is}(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{ist} \quad (4.5)$$

where $t_1 < t_2$ and $t_1, t_2 \in$ (event window).

And for the purpose of this study, where I am interested in the sectoral abnormal returns in response to the French carbon tax announcement, I calculate the average abnormal returns (AAR)

in each sector:

$$AAR_{st} = \frac{1}{N} \sum_{i=1}^N AR_{ist} \quad (4.6)$$

where AAR_{st} is the average abnormal returns for sector s at time t . In a similar fashion for event windows with multiple days, we should aggregate $AARs$ for each day in the event window to calculate the cumulative average abnormal returns:

$$CAAR(t_1, t_2)_s = \sum_{t=t_1}^{t_2} AAR_{s,t} \quad (4.7)$$

where $t_1 < t_2$ and $t_1, t_2 \in$ (event window) and $CAAR(t_1, t_2)_s$ is the cumulative average abnormal returns for sector s during the event window from t_1 to t_2 .

In the next section, I describe the data that I use to estimate the AAR and $CAAR$ values for each sector and in section 4.6, I present the results for the estimated models.

4.5 Data

The firm level equity data for this study includes the daily returns of shares of 891 publicly traded firms in Euronext Paris Stock Exchange (including Growth and Access Paris exchanges) spanning more than two years between January 1, 2017 and July 1, 2019. I obtained the daily opening and closing prices of these equities from the Bloomberg terminal. As I am interested in the relationship between energy intensity and abnormal market returns in response to the French carbon tax announcement event, I use a subset of Euronext equities for firms in the manufacturing sector which creates a sample of 151 firms. Euronext Paris stock exchange provides several indices, including the Premier Marché for large cap French companies, Second Marché for mid-cap firms and Nouveau Marché for fast-growing small-cap startups. For this analysis I will use the Euronext 100 index as

the benchmark which is the capitalization-weighted index of 100 blue-chip French companies. This index is equivalent to the S&P 500 in the U.S..¹³

The daily closing values for the Euronext 100 Index can be seen in Figure 4.3 between January 1, 2018 and July 1, 2019. The daily returns of the Index are in Figure 4.4. As we can see in these two figures, the Index experienced one of its sharpest daily decreases on the day of the announcement and this makes it crucial to implement the CAPM adjustment with excess market returns to AR values for each firm. In Figure 4.5, we see the sharp decrease in the index more clearly when we overlay the 3-day event window, including the day before and after the December 4 announcement, on the Euronext 100 Index values. This figure shows that the 3-day event window coincides with a highly sharp drop in the index values.

For the CAPM-adjusted and MF models, I use the Euro Overnight Index Average (EONIA) as the risk-free rate which was the one-day interbank interest rate for the Euro zone or the rate which banks provided loans to each other with a duration of one day. I get the daily EONIA rates from European Central Bank's Statistical Data Warehouse.¹⁴ It should be noted that after the recommendation of The Working Group on Euro Risk-Free Rates of European Securities and Markets Authority (ESMA), EONIA was replaced with Euro Short-Term Rate (ESTER) after 2021.¹⁵ For the MF model, I use the Fama-French European 3-factors from Kenneth French's data library (French 2022). Unfortunately, the data library does not have a 3-factor dataset specific to the French equity markets and the closest equity market I could benchmark the French equity performance with is the European markets.

¹³A benchmark for the Euronext Paris stock exchange with a narrower scope is CAC 40 which is the capitalization-weighted index of the 40 largest companies listed in Euronext Paris. It could be seen as France's equivalent to Dow Jones Industrial Average (DJIA).

¹⁴To access the ECB's Statistical Data Warehouse, see <https://sdw.ecb.europa.eu/>.

¹⁵To access The Working Group's website, see: <https://www.esma.europa.eu/policy-activities/benchmarks/working-group-euro-risk-free-rates>.

To generate energy intensity at the sectoral level, I use energy used by each sector in tonnes of oil equivalent and value added generated by each manufacturing sector. I use French Statistical Institute's (INSEE) Annual Survey on Industrial Consumption (EACEI) data for the nationally representative sample of firms in France in 2018. This survey provides the quantities consumed by type of energy, related costs, and the breakdown by each energy used.¹⁶ For value added created by manufacturing sectors, I use INSEE's annual sectoral survey (ESA) in 2018.¹⁷ To generate the energy intensity variable, I divide the total energy used by each sector with the value added generated by each sector in 2018. Figure 4.6 ranks industries with respect to this estimated energy intensity variable. Among the top three energy intensive industries, non-metal minerals sector includes, cement, ceramics, glass and also oil and gas sub-sectors, basic metals sector includes iron, steel, aluminum and other intermediate goods sub-sectors and chemicals sector includes petrochemicals, polymers, basic inorganics and consumer chemicals sub-sectors.

To categorize manufacturing firms into sectors and sub-sectors for energy intensity INSEE surveys use NACE classification¹⁸ which is the European Union equivalent of the NAICS classification system in the U.S.. I also use Bloomberg Industrial Classification System (BICS) to match firm-level equity data with energy intensity by sectors and sub-sectors.

4.6 Findings

To estimate the event studies with equity data, beyond manually calculating average and cumulative abnormal returns for each sector and their standard errors, there are several automated options

¹⁶For details of the EACEI survey, see: <https://www.insee.fr/en/metadonnees/source/serie/s1214>

¹⁷For details of the ESA survey, see: <https://www.insee.fr/en/metadonnees/source/serie/s1269>.

¹⁸NACE is an abbreviation for *Nomenclature des Activités Économiques dans la Communauté Européenne*, which translates to English as "Statistical Classification of Economic Activities in the European Community".

in Stata (Kaspereit 2021). Among these options, I use the `eventstudy2` and `estudy` packages to estimate the abnormal returns for different sectors (Kaspereit 2020, Pacicco et al. 2018).

Among the 21 sectors with energy intensity values calculated, I estimate the *AARs* and *CAARs* for 15 manufacturing sectors with more than one firm actively traded in the Euronext Paris. There are no firms traded for the leather sector in my sample and the trading volumes for three firms traded for wood products and furniture sectors were quite thin to estimate abnormal returns in the event windows. Also I aggregated motor vehicles and other transport vehicles sectors as their energy intensities are very similar to each other (see Figure 4.6) and other transport vehicles sector had a single firm in the sample.

The estimated of *AARs* and *CAARs* with CAPM-adjustment are presented in Table 4.2 and results estimated with multi factor adjustment are presented in Table 4.3. The first column shows the number of firms in each sector, the second column presents the *AARs* in the 1-day event window on the day of announcement, December 4, 2018. Columns 3, 4 and 5 presents *CAARs* for event windows spanning multiple days. Column 6 includes results of the placebo test that I describe below.

Overall, the results indicate that energy intensive firms benefited from the market reaction to the French carbon tax announcement while firms with lower energy intensity were at a disadvantage. All three top energy intensive sectors (non-metal minerals, basic metals and chemicals) have positive and statistically significant *AARs* and *CAARs* in 1-day and 3-day event windows. On average, firms in non-metal minerals, basic metals and chemicals sectors had excess returns above 1% in the CAPM-adjusted model and MF model with 1-day and 3-day event windows. When we implement 5-day and 10-day event windows to test the efficient market hypothesis, we see that equities in these sectors do not respond to the abnormal returns during and after the announcement with

mean reversion in the following days. Among other high energy intensive firms, paper and textiles sectors did not have significant results, probably due to limited number of equities traded in these sectors.

As the energy intensity of the sectors decreases, we see that estimated *AAR* and *CAAR* values turn negative with high statistical significance. While the *AARs* for pharmaceuticals, motor vehicles, wearing apparel, machinery, electrical equipment and electronics sectors are in the range of -0.5% to -4% with CAPM-adjusted model, *CAARs* estimated with same model in the 3-day event window are much higher, ranging from -2% to -8%. With longer 5-day and 10-day event windows, we see that the magnitudes of negative *CAARs* increase substantially. For instance for the pharmaceuticals sector, estimated *CAARs* are -9% and -7.52% for 5 and 10 day event windows respectively and electrical equipment industry these values are -9.03% and 6.77%. The magnitude of the *CAAR* estimates with the MF model are lower but the statistical significance and signs of the coefficient estimates are similar to those from CAPM-adjusted model. This might be due to the Europe-wide equity benchmarks I am using for this model instead of French stock market benchmarks.

For event windows spanning several days and averaged across individual firm returns within sectors, ignoring contemporaneous correlations across firm level returns may introduce downward bias in the standard deviation which overestimates the t-statistic and leads to over-rejection of the null hypothesis (Kolari and Pynnönen 2010). For the hypothesis test where null is $H_0 : E(CAAR(t_1, t_2)_s) = 0$, along with the t-test, I also run the two parametric event study tests: the standardized residual test (Patell Z) and the adjusted standardized residual test (adjusted Patell Z) formulated by Patell (1976) and Kolari and Pynnönen (2010). The significance levels of the coefficient estimates in Tables 4.2 and 4.3 do not change with these two tests.

In the last column, I run a placebo test to gauge the surprise factor in the French carbon tax announcement by running the models with an event window starting 10 days before the event and ending 2 days before. If there are any abnormal returns within this event window, we should be cautioned about the unexpected nature of the event. When we look at the results in column 5 in Tables 4.2 and 4.3 we see that none of the sectors had abnormal returns at statistically significant levels. The parametric event study tests described above also do not alter the insignificance of the coefficient estimates. This provides a good reason for us to be convinced that the policy reversal was indeed an unexpected one for the stock market participants.

Figures 4.7 and 4.8 show the CAPM-adjusted *AARs* for 1-day and *CAARs* for 3-day event windows for each manufacturing sector plotted against the energy intensity of these sectors. The red lines in these plots show the linear lines of best fit and they indicate a clear positive relationship between the energy intensity and abnormal returns of sectors. We encounter a very similar picture in Figures 4.9 and 4.10, where we see the *AARs* and *CAARs* for each manufacturing sector plotted against the energy intensity of these sectors. The slopes of the lines of best fit have a slightly lower slope probably due to effect of the two additional factors we add into the MF models. In these plots, we clearly see that investors diverted from less energy intensive sectors to the more energy intensive ones immediately after the announcement of the French carbon tax rate increase suspension. The most plausible explanation is that investors were convinced that policies to attain France's ambitious decarbonization goals especially those complementing or enhancing the coverage of EU ETS would not be implemented at a fast pace after the setback following the Yellow Vests protests. Market participants probably anticipate that energy intensive sectors will have higher profits than previously estimated and less energy intensive sectors benefiting from environmental and climate regulations will not be able to generate the profits previously anticipated.

4.7 Discussion and Conclusion

The announcement to suspend the French carbon tax rate increase was unexpected. The French public did not expect it, the investors did not expect it and probably looking at official statements, the government itself did not expect the policy reversal in the French carbon tax rate. Yet, it had repercussions for the long term environmental, climate and decarbonization strategies of France. In this paper, I showed that stock prices responded to the anticipation of a slower pace in the progress of French climate policy by rewarding energy intensive firms and punishing less energy intensive ones. Results of this paper's analysis suggest that changes in the expectations about environmental policy stringency have significant impacts on corporate performance proxied by equity prices even if the actual changes in environmental regulations are not directly applicable to the firms of these equities. Energy-intensive firms may enjoy excess positive returns and low energy intensive firms may suffer from excess negative returns even if environmental policy changes do not affect them directly.

For future research, a first extension of this analysis could be testing a potential "boomerang" effect. Investors could have anticipated a slow down in the ambitious climate policies in the short-run after carbon tax rate suspension. But they might also have considered that this was transitory and the government would continue increasing the stringency in decarbonization efforts in the long run. Certain events, such as the decision to initiate Citizen's Convention for the Climate Change that show French governments' determination to achieve its climate targets might have the opposite effect that we see after the carbon tax rate announcement. Examining stock market responses in the aftermath of such events could be instrumental in understanding whether investors update their beliefs with the anticipation of another wave of environmental policy stringency.

While informative, the quantitative analysis in this paper is limited only to publicly traded

firms which is a fraction of the universe of firms in France. To estimate the broader impacts of this policy shift, future research can focus on the corporate performance of private firms in terms of profitability, employment, investments and energy expenditure. A comparison of firms directly affected by the policy reversal in carbon tax rates with respect to their degree of energy intensities could be conducive in understanding the firm-level effects outside of the publicly traded firms.

4.8 Figures and Tables

4.8.1 Figures

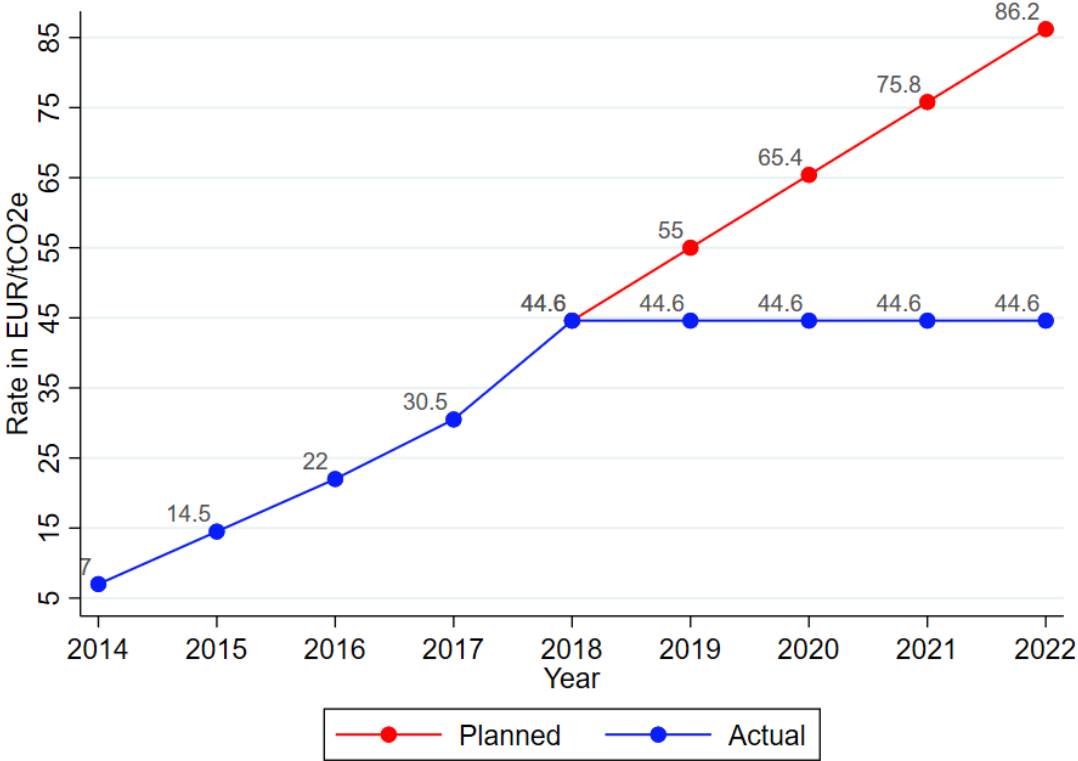


Figure 4.1: Change in French carbon tax trajectory at the end of 2018

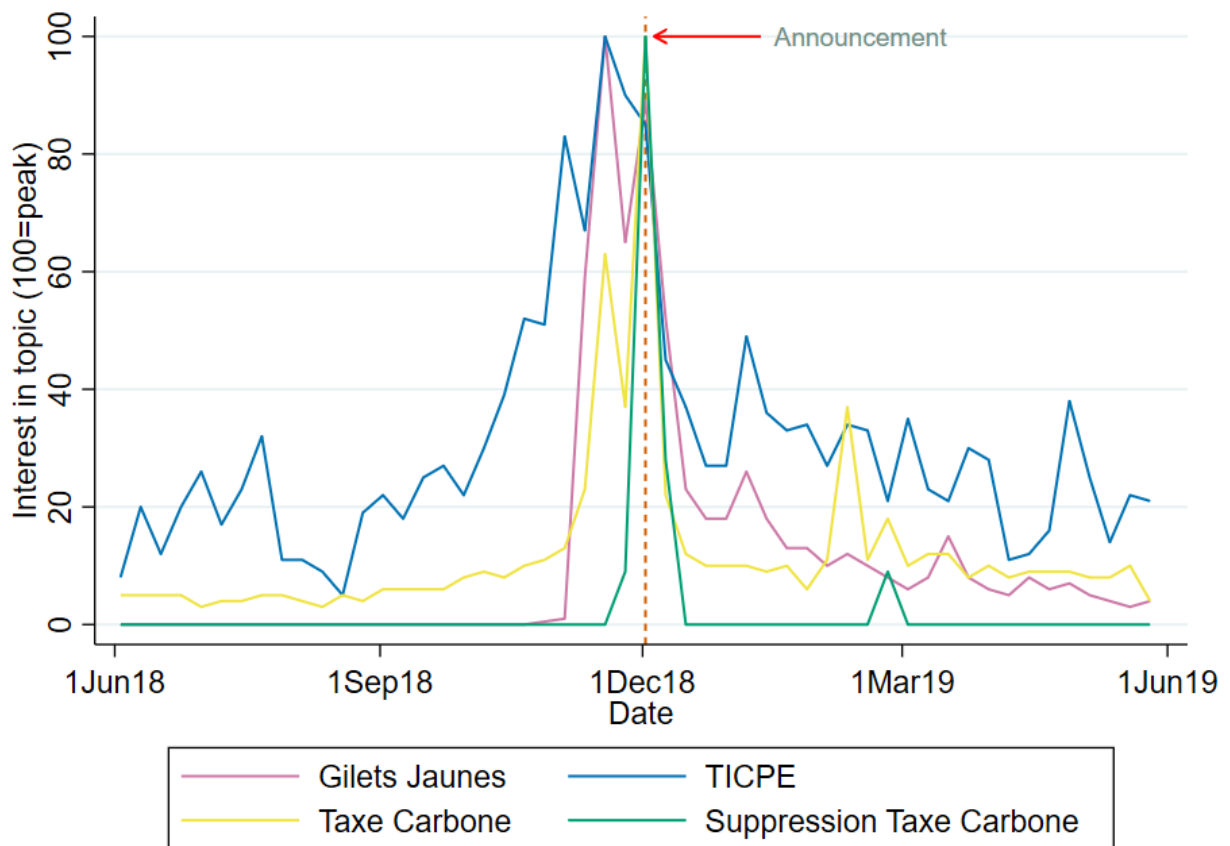


Figure 4.2: Google search trends for popular phrases during protests. Phrases “Taxe Carbone” (carbon tax), “Gilets Jaunes” (Yellow Vests), “TICPE” (abbreviation for the energy tax) and “Suppression tax carbone” (suspension of carbon tax) in France between 6/1/2018 - 6/1/2019 in 0-100, 100 indicating maximum interest in the topic on Google searches.

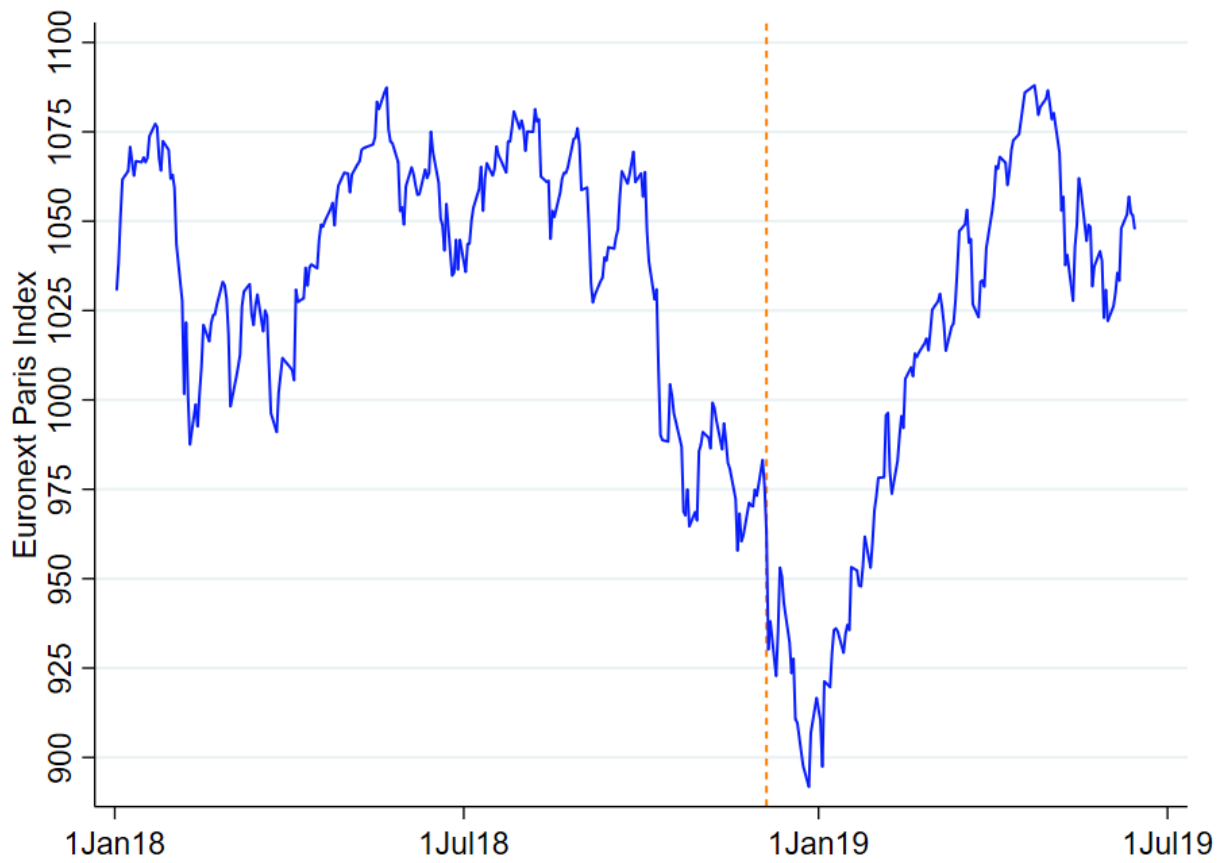


Figure 4.3: Euronext Paris Index daily closing values between 11/30/2017 – 12/31/2019. Orange dashed line indicates the event date, December 4, 2018.

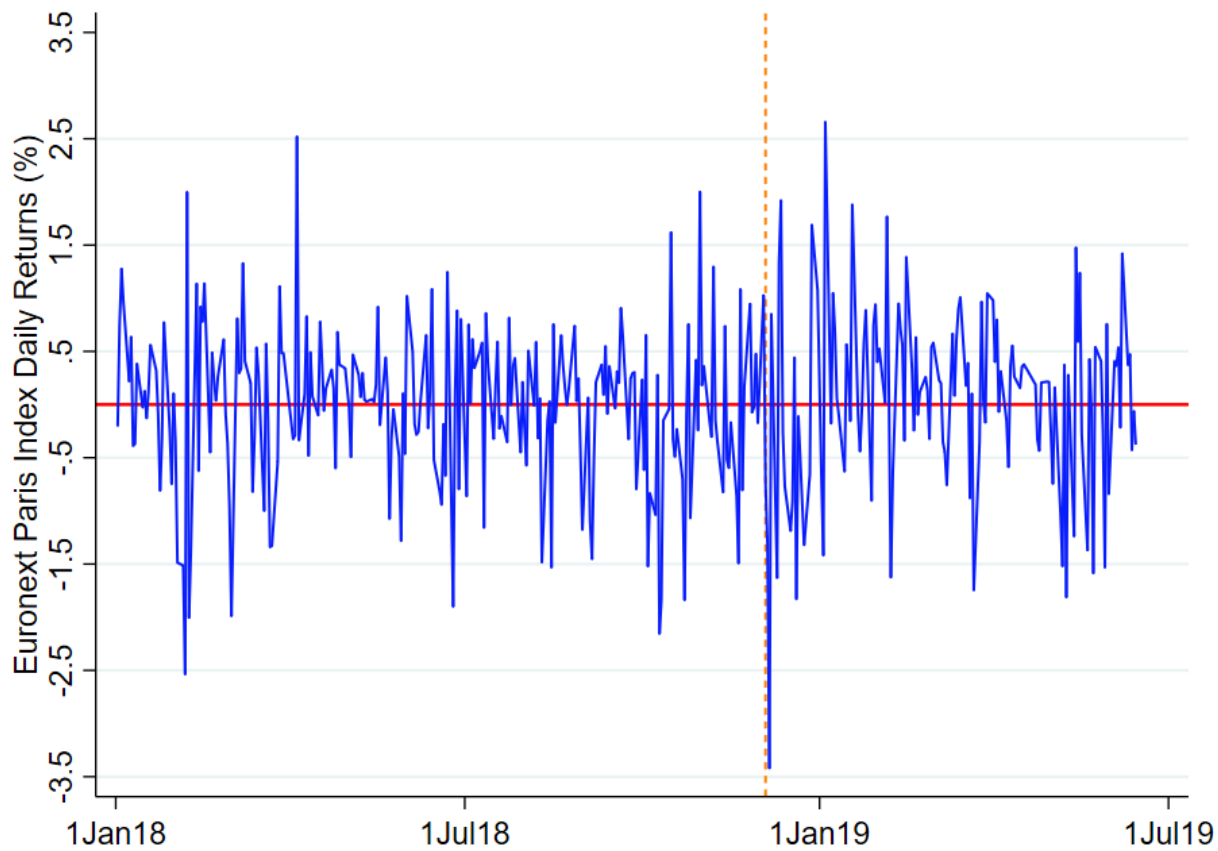


Figure 4.4: Euronext Paris Index daily returns between 1/1/2018 – 7/1/2019. Orange dashed line indicates the event date, December 4, 2018.

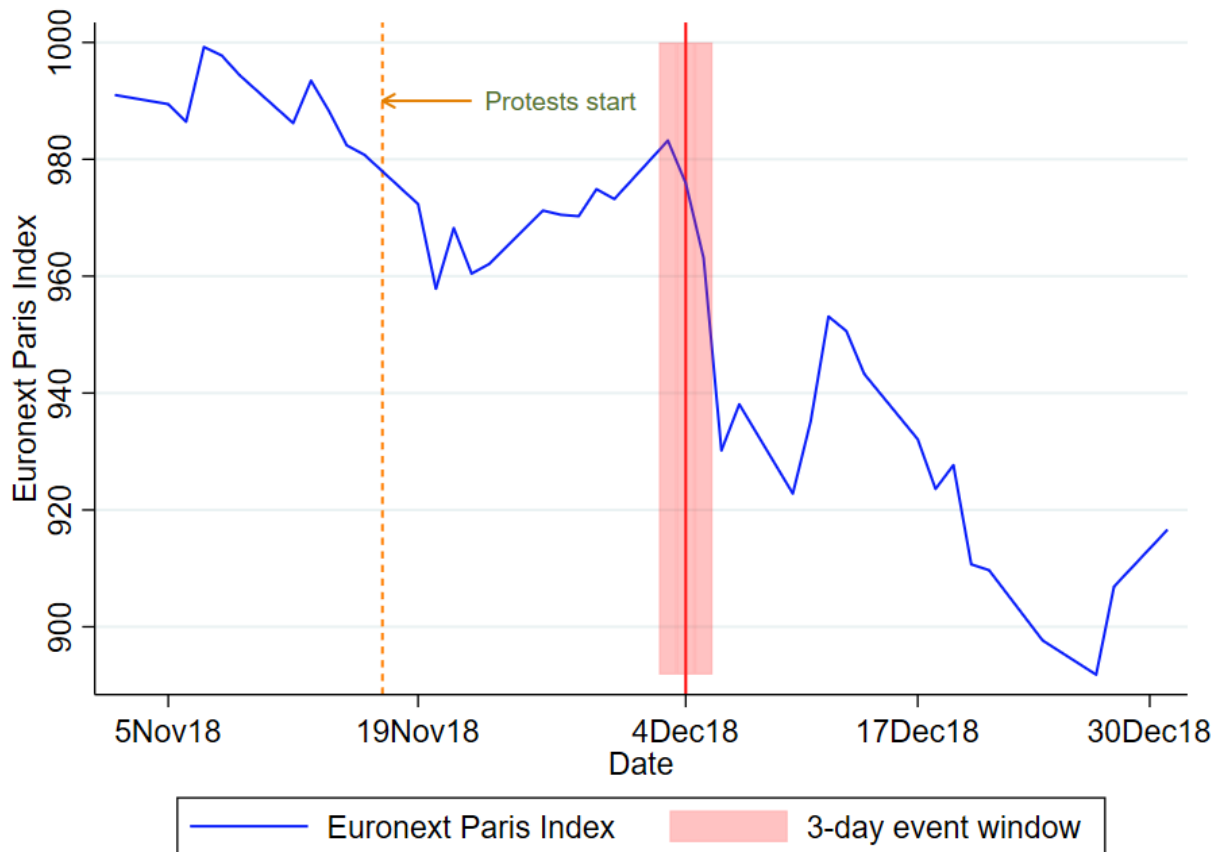


Figure 4.5: Euronext Paris Index returns between November 1, 2018 – December 31, 2018. The event day (solid red line), the 3-day event window and the beginning of protests (dashed orange line).

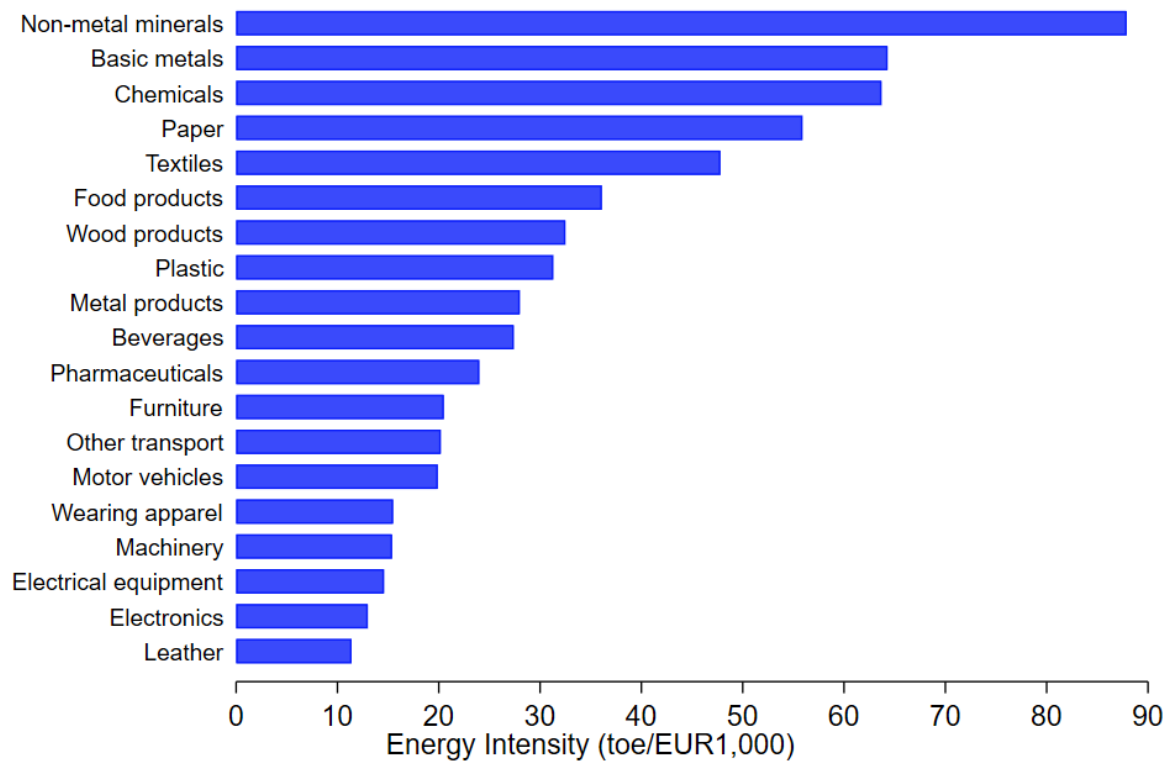


Figure 4.6: Energy intensities of French manufacturing sectors in tonnes of oil equivalent for 1,000 Euros of value added.

Source: INSEE, Odyssee Database and author's calculation.

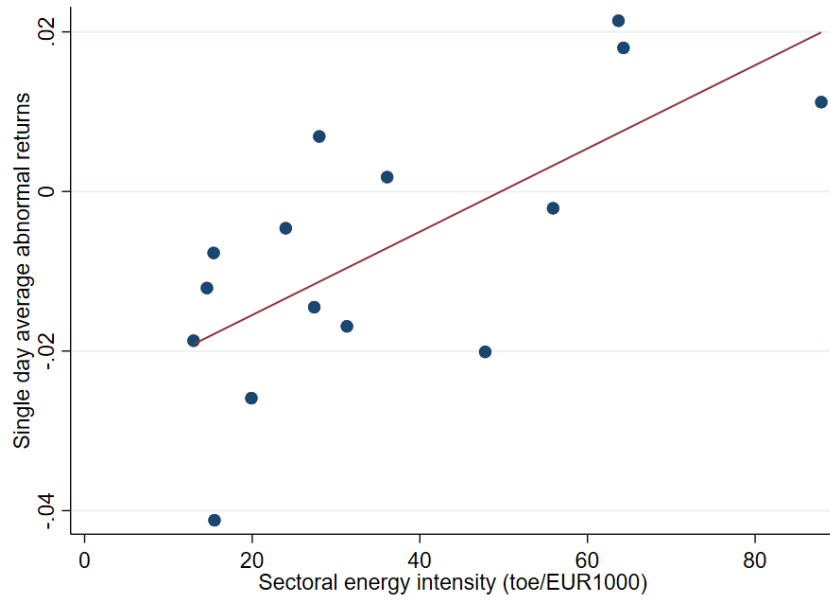


Figure 4.7: Energy intensity vs 1-day AAR (Single factor)

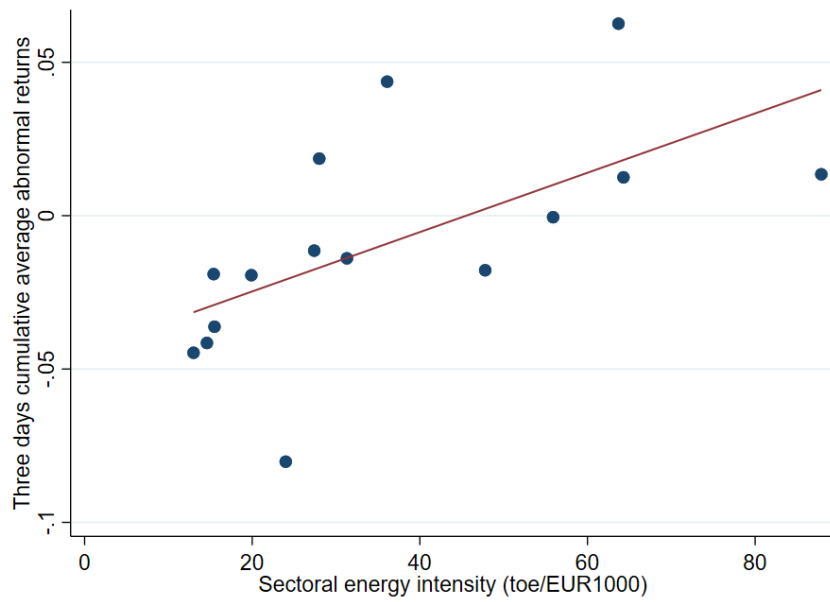


Figure 4.8: Energy intensity vs 3-days CAAR (Single factor)

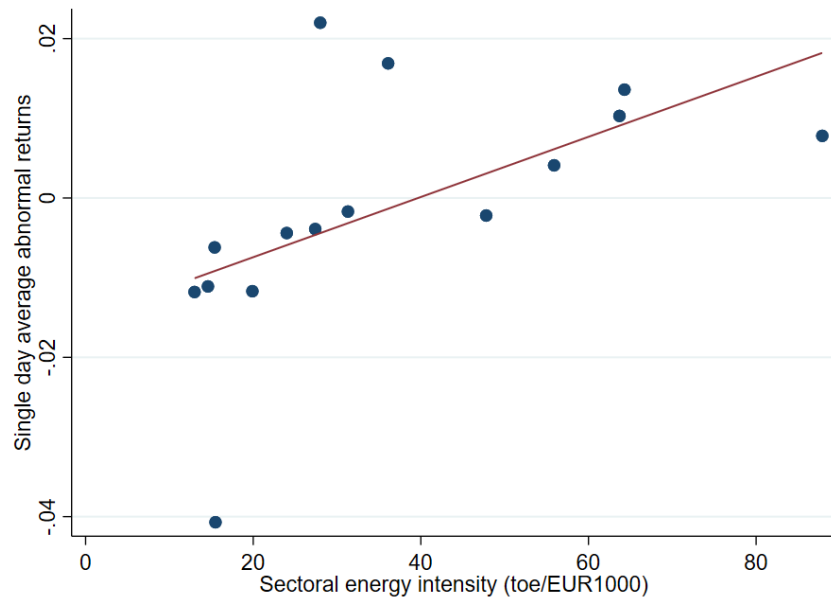


Figure 4.9: Energy intensity vs 1-day AAR (Fama-French 3-factor)

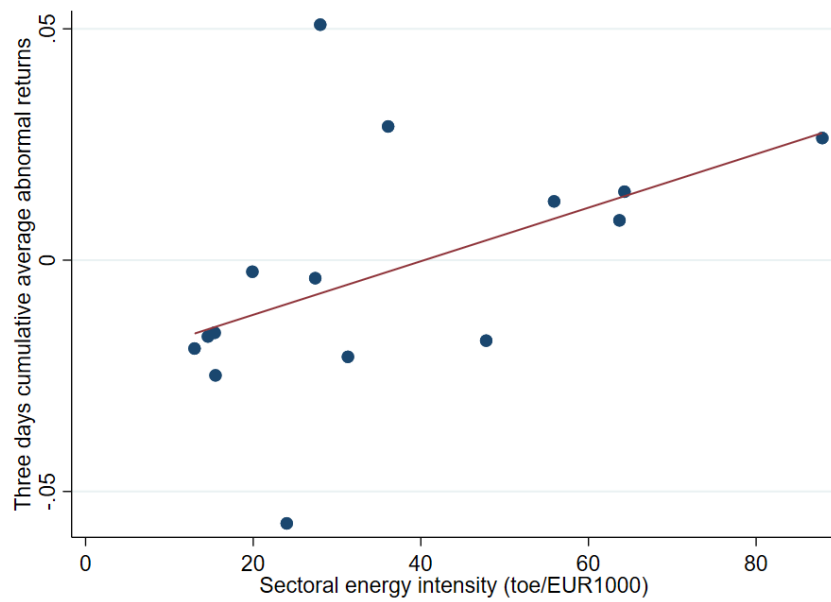


Figure 4.10: Energy intensity vs 3-days CAAR (Fama-French 3-factor)

4.8.2 Tables

Table 4.1: Timeline of events during Yellow Vests protests

Date	Event
18 October 2018	Jacline Mouraud's video goes viral
17 November 2018	First day of motorblockades with 290,000 protestors
18 November 2018	Government announces it will not back down on fuel tax increases
24 November 2018	Large-scale demonstrations in Paris, clashes on Champs-Elysees
27 November 2018	Macron offers a mechanism to adjust fuel tax increases
29 November 2018	French PM's proposed meeting with protestors is cancelled
1 December 2018	Violent clashes between protestors and the police in Paris and other large cities
2 December 2018	Macron assembles a crisis meeting with ministers at the Elysee Palace
3 December 2018	French PM meets with political party leaders
4 December 2018	French PM announces the 6-month suspension of the planned carbon tax increase

Table 4.2: CAAR and AAR returns by manufacturing sectors after policy reversal

Sectors	(1)	(2)	(3)	(4)	(5)	(6)
	Number of firms	AAR 1-day (t)	CAAR			
			3-day ($t-1:t+1$)	5-day ($t-2:t+2$)	10-day ($t-5:t+4$)	Placebo ($t-10:t-2$)
Non-metal minerals	11	0.0112** (0.0049)	0.0135*** (0.0022)	0.0214** (0.0061)	0.0515*** (0.0144)	0.0026 (0.0435)
Basic metals	7	0.0180* (0.0094)	0.0125* (0.0065)	0.0074** (0.0028)	0.0035* (0.0017)	0.01421 (0.0947)
Chemicals	10	0.0214** (0.0087)	0.0626*** (0.0128)	0.0481*** (0.0098)	0.0885*** (0.0152)	0.0239 (0.0587)
Paper	2	-0.0021 (0.0019)	-0.0005 (0.0006)	-0.0124 (0.0218)	0.0095 (0.0107)	0.0168 (0.0248)
Textiles	2	-0.0201 (0.0212)	-0.0178 (0.0207)	-0.0269 (0.0293)	0.0001 (0.0003)	-0.0074 (0.0089)
Food products	22	0.0018*** (0.0005)	0.0437*** (0.0112)	0.0499*** (0.0109)	0.0505*** (0.0105)	-0.0077 (0.0094)
Plastic	3	-0.0169* (0.0068)	-0.0139* (0.0054)	-0.0637** (0.0179)	-0.0625* (0.0243)	0.0021 (0.0041)
Metal products	3	0.0069* (0.0027)	0.0186* (0.0069)	-0.0353 (0.0166)	-0.0582 (0.0271)	0.0881 (0.0701)
Beverages	9	-0.0145* (0.0064)	-0.0114** (0.0046)	-0.0262** (0.0107)	-0.0348** (0.0136)	0.0051 (0.0061)
Pharmaceuticals	17	-0.0046* (0.0022)	-0.0802*** (0.0138)	-0.0900*** (0.0153)	-0.0752*** (0.0126)	0.0389 (0.0472)
Motor vehicles	10	-0.0259** (0.0097)	-0.0194** (0.0073)	-0.0435*** (0.0136)	-0.0622* (0.0317)	-0.0073 (0.0185)
Wearing apparel	13	-0.0412* (0.0211)	-0.0362** (0.0140)	-0.0671*** (0.0183)	-0.0017* (0.0009)	0.0033 (0.0034)
Machinery	18	-0.0077* (0.0042)	-0.01905* (0.0104)	-0.0167* (0.009)	-0.0424* (0.0232)	-0.0076 (0.0129)
Electrical equipment	7	-0.0121* (0.0060)	-0.0415* (0.0204)	-0.0903*** (0.0238)	-0.0677*** (0.0183)	0.0428 (0.0641)
Electronics	17	-0.0187** (0.0078)	-0.0447* (0.0213)	-0.0301*** (0.0086)	-0.0561** (0.0224)	0.0158 (0.0153)

AARs and CAARs are CAPM-adjusted with single market index. Standard errors from t-test are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.3: CAAR and AAR returns by manufacturing sectors after policy reversal

Sectors	(1)	(2)	(3)	(4)	(5)	(6)
	Number of firms	AAR 1-day (t)	CAAR			
			3-day ($t-1:t+1$)	5-day ($t-2:t+2$)	10-day ($t-5:t+4$)	Placebo ($t-10:t-2$)
Non-metal minerals	11	0.0078** (0.0031)	0.0264*** (0.0068)	0.0182** (0.0077)	0.0511*** (0.0105)	0.0133 (0.389)
Basic metals	7	0.0136* (0.0071)	0.0148* (0.0076)	0.0065* (0.0032)	0.0467 (0.0261)	0.0292 (0.0257)
Chemicals	10	0.0103** (0.0042)	0.0086* (0.0041)	0.0189* (0.0088)	0.0247* (0.0114)	0.0067 (0.081)
Paper	2	0.0041 (0.0031)	0.0127 (0.0106)	-0.0070 (0.0057)	-0.0022 (0.0018)	-0.0232 (0.0337)
Textiles	2	-0.0022 (0.0019)	-0.0174 (0.0163)	0.0301 (0.0281)	0.0188 (0.0146)	0.0221 (0.0762)
Food products	22	0.0169*** (0.0043)	0.0289*** (0.0092)	0.0319** (0.0129)	0.0233 (0.0146)	-0.0168 (0.0258)
Plastic	3	-0.0017* (0.0006)	-0.0209* (0.0067)	-0.0116* (0.0038)	-0.0046* (0.0015)	0.0248 (0.0117)
Metal products	3	0.0220 (0.0099)	0.0509* (0.0212)	-0.0363 (0.0177)	-0.0718 (0.0381)	0.0974 (0.1384)
Beverages	9	-0.0039* (0.0019)	-0.0039** (0.0016)	-0.0064** (0.0026)	-0.0127** (0.0049)	-0.0051 (0.0126)
Pharmaceuticals	17	-0.0044* (0.0021)	-0.0569*** (0.0121)	-0.0431** (0.0165)	-0.0321* (0.0168)	0.0429 (0.0512)
Motor vehicles	10	-0.0117** (0.0051)	-0.0025* (0.0013)	-0.0088* (0.0048)	-0.0453** (0.0196)	-0.0035 (0.0055)
Wearing apparel	13	-0.0407*** (0.0113)	-0.0249*** (0.0065)	-0.0306* (0.0145)	-0.0422* (0.0213)	0.0193 (0.0157)
Machinery	18	-0.0062* (0.0034)	-0.0157* (0.0085)	-0.0113* (0.0059)	-0.0143* (0.0074)	0.0137 (0.0216)
Electrical equipment	7	-0.0111* (0.0056)	-0.0165* (0.0083)	-0.0155** (0.0058)	-0.0012** (0.0004)	0.0069 (0.0094)
Electronics	17	-0.0118** (0.0055)	-0.0191* (0.0101)	-0.0091*** (0.0025)	-0.0161** (0.0049)	0.0404 (0.0322)

AARs and CAARs are CAPM-adjusted with Fama-French 3-factors. Standard errors from t-test are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Chapter A
APPENDICES

A.1 Figures

A.1.1 Appendix figures for Chapter 2

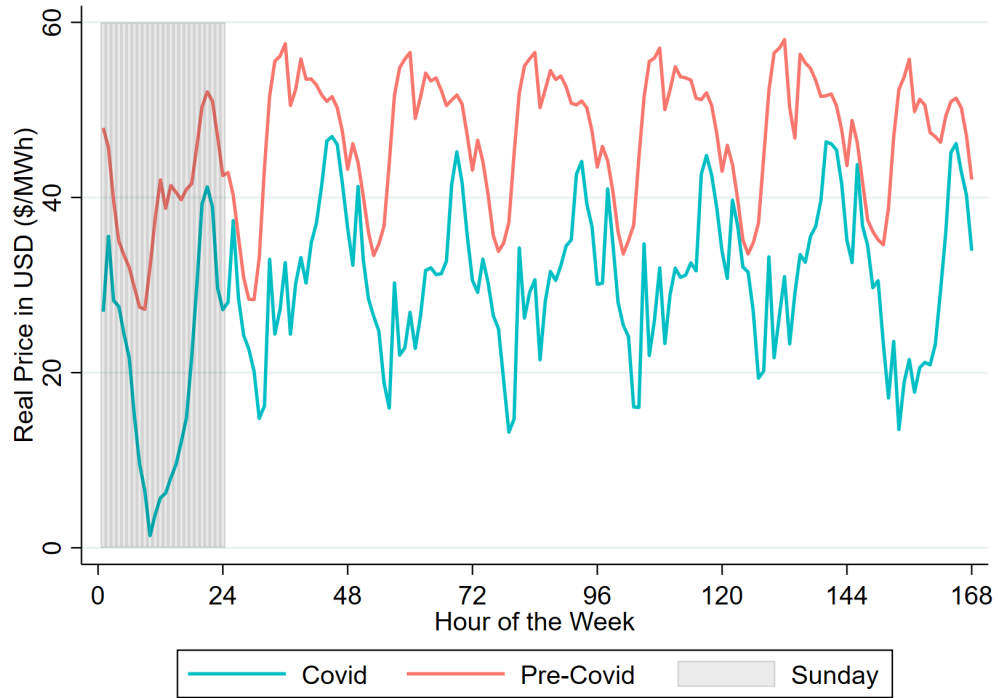


Figure A2.1: Average day-ahead market price in USD/MWh by hour of the week before and during Covid-19 lockdowns.

A.1.2 Appendix figures for Chapter 3



Figure A3.1: Location of the Williston Basin at the border of United States and Canada. Source: [Kuhn et al. \(2012\)](#).

A.1.3 Appendix figures for Chapter 4

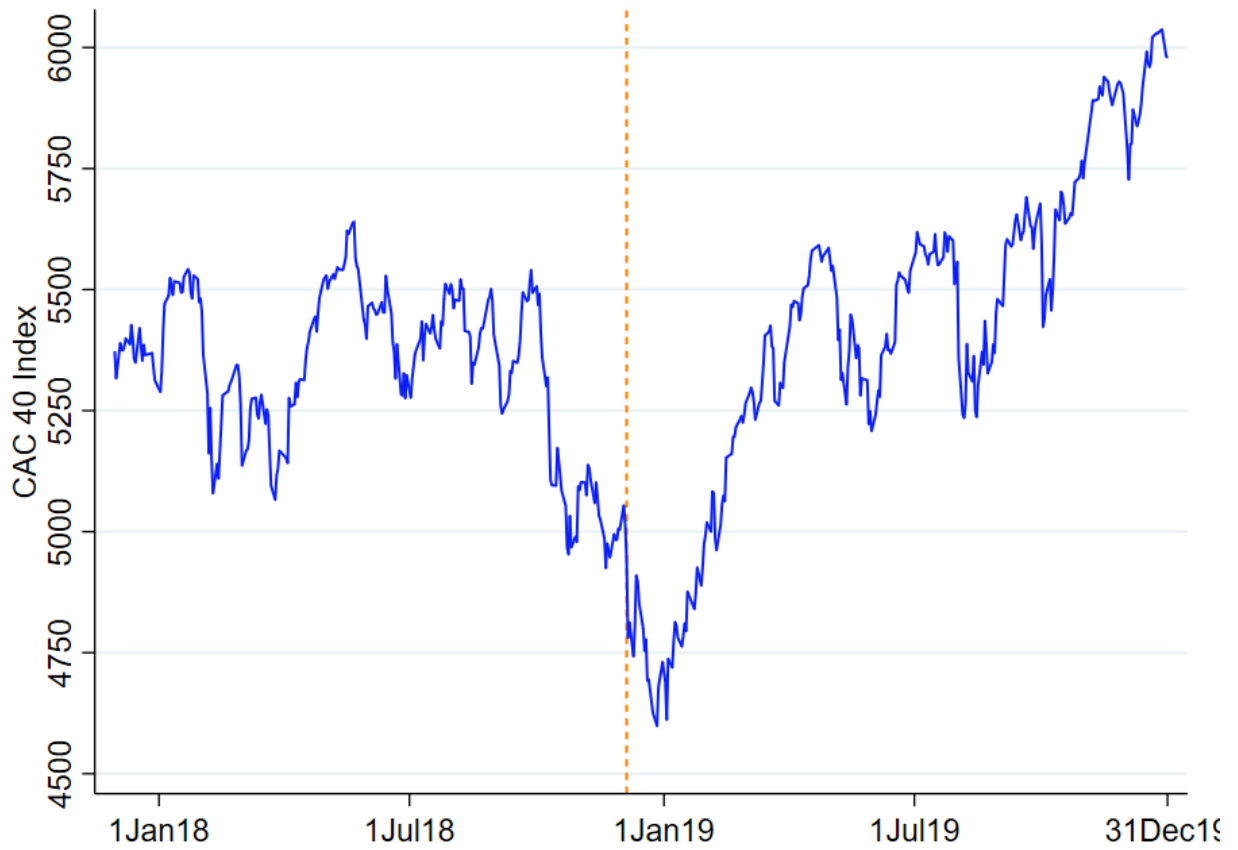


Figure A4.1: CAC 40 Index values between 11/30/2017 – 12/31/2019. Orange dashed line indicates the event date, December 4, 2018.

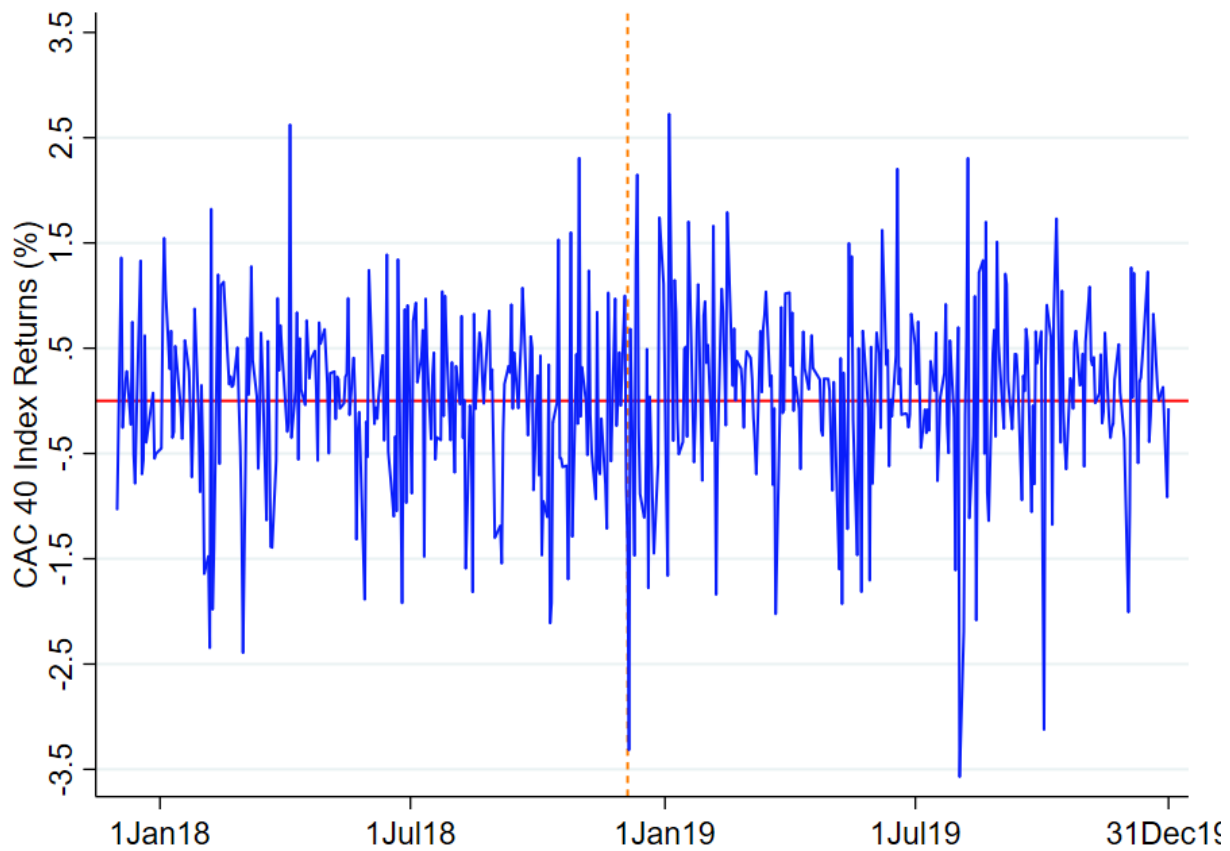


Figure A4.2: CAC 40 Index returns between 11/30/2017 – 12/31/2019. Orange dashed line indicates the event date, December 4, 2018.

A.2 Tables

A.2.1 Appendix tables for Chapter 2

Table A2.1: Merit order effect of wind energy

VARIABLES	(1) Pre-Covid19	(2) Full-Panel	(3) Full-Panel
Ln(Wind)	-0.1680*** (0.0087)	-0.1683*** (0.0090)	-0.1682*** (0.0090)
Ln(Wind) \times Covid		0.0368*** (0.0126)	0.0374*** (0.0133)
$f(D) \times$ Covid	Yes	Yes	Yes
Observations	36,831	38,525	38,525
R-squared	0.7483	0.7594	0.7597

Dependent variable is the natural log of hourly price of 1 MWh of electricity in the day-ahead markets in Turkish liras.

Newey-West standard errors with 24 hours lag are in parentheses.

For statistical significance, *** p<0.01, ** p<0.05, * p<0.1.

A.2.2 Appendix tables for Chapter 3

Table A3.1: OLS Models with Levels

VARIABLES	(1) Prod - H	(2) Prod - V	(3) Prod - H	(4) Prod - V	(5) Prod - H	(6) Prod - V
Production (t-1)	0.7064*** (0.0034)	0.8187*** (0.0392)	0.7059*** (0.0034)	0.8214*** (0.0395)	0.7059*** (0.0034)	0.8214*** (0.0395)
Production (t-2)	0.1032*** (0.0031)	0.1549*** (0.0380)	0.1014*** (0.0031)	0.1520*** (0.0382)	0.1014*** (0.0031)	0.1520*** (0.0382)
PC Negative	-11.6456*** (0.4484)	-0.8019*** (0.0663)	-412.3378*** (92.1797)	-40.2172*** (4.5215)	-398.2157*** (89.2547)	-37.2172*** (3.1851)
PC Positive	-4.1786*** (0.5895)	-0.3774*** (0.0980)	-99.6812*** (21.8083)	-9.5679*** (1.0775)	-93.7541*** (19.7589)	-8.8732*** (1.2126)
Constant	411.7934*** (3.5563)	8.8606*** (1.4274)	1,257.9308*** (214.1263)	97.7796*** (10.0871)	-1224.1228*** (245.7067)	73.9163*** (8.9236)
Observations	1,608,958	1,065,735	1,608,958	1,065,735	1,608,958	1,065,735
R-squared	0.7297	0.9613	0.7312	0.9616	0.7312	0.9616
Well Dummies	No	No	Yes	Yes	Yes	Yes
Month Dummies	No	No	Yes	Yes	No	No
Macro Controls	No	No	No	No	Yes	Yes

Dependent variable is the monthly oil production in barrels.

Robust standard errors clustered at the well and month level in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

Table A3.2: OLS Models with Logs

VARIABLES	(1) Ln(Prod) - H	(2) Ln(Prod) - V	(3) Ln(Prod) - H	(4) Ln(Prod) - V	(5) Ln(Prod) - H
$Ln(Prod_{t-1})$	0.6750*** (0.0017)	0.6730*** (0.0023)	0.6677*** (0.0017)	0.6682*** (0.0023)	0.6677*** (0.0017)
$Ln(Prod_{t-2})$	0.1251*** (0.0015)	0.2717*** (0.0023)	0.1280*** (0.0015)	0.2737*** (0.0023)	0.1280*** (0.0015)
PC Negative	-0.0571*** (0.0019)	-0.0335*** (0.0017)	-0.0747*** (0.1876)	-0.0213*** (0.0050)	-0.0688*** (0.0021)
PC Positive	-0.0428*** (0.0019)	-0.0247*** (0.0017)	-0.0624*** (0.0158)	-0.0169*** (0.00380)	-0.0534*** (0.0142)
Constant	0.8915*** (0.0134)	-0.1004*** (0.0111)	-2.5966*** (0.9347)	-0.9434*** (0.2641)	-16.0180** (6.9332)
Observations	1,608,922	1,065,711	1,608,922	1,065,711	1,608,922
R-squared	0.6098	0.8586	0.6157	0.8599	0.6157
Well Dummies	No	No	Yes	Yes	Yes
Month Dummies	No	No	Yes	Yes	No
Macro Controls	No	No	No	No	Yes

Dependent variable is the natural log of the monthly oil production in barrels.

Robust standard errors clustered at the well and month level in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

Table A3.3: OLS Models with IHS

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Ihs(Prod) - H	Ihs(Prod) - V	Ihs(Prod) - H	Ihs(Prod) - V	Ihs(Prod) - H	Ihs(Prod) - V
<i>IHS(Prod_{t-1})</i>	0.7145*** (0.0016)	0.7131*** (0.0023)	0.7064*** (0.0016)	0.7086*** (0.0023)	0.7064*** (0.0016)	0.7086*** (0.0023)
<i>IHS(Prod_{t-2})</i>	0.1009*** (0.0015)	0.2392*** (0.0023)	0.1033*** (0.0015)	0.2413*** (0.0023)	0.1033*** (0.0015)	0.2413*** (0.0023)
PC Negative	-0.0669*** (0.0016)	-0.0394*** (0.0014)	-0.5648*** (0.1050)	-0.1779*** (0.0303)	-0.0389** (0.0165)	-0.0281 (0.0379)
PC Positive	-0.0246*** (0.0017)	-0.0112*** (0.0013)	-0.2957*** (0.0555)	-0.0777*** (0.0138)	-0.0199*** (0.0029)	-0.0183 (0.0248)
Constant	1.4062*** (0.0074)	0.2353*** (0.0028)	2.1686*** (0.1653)	0.4583*** (0.0297)	-11.1011*** (4.1800)	5.8141 (9.5830)
Observations	1,608,958	1,065,735	1,608,958	1,065,735	1,608,958	1,065,735
R-squared	0.6451	0.8819	0.6512	0.8831	0.6512	0.8831
Well Dummies	No	No	Yes	Yes	Yes	Yes
Month Dummies	No	No	Yes	Yes	No	No
Macro Controls	No	No	No	No	Yes	Yes

Dependent variable is the hyperbolic sine transformed monthly oil production in barrels.

Robust standard errors clustered at the well and month level in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

Table A3.4: FE Models with levels

VARIABLES	(1) Prod - H	(2) Prod - V	(3) Prod - H	(4) Prod - V
Production (t-1)	0.6451*** (0.0034)	0.8149*** (0.0318)	0.6231*** (0.0031)	0.8015*** (0.0311)
Production (t-2)	0.0588*** (0.0031)	0.1462*** (0.0305)	0.0554*** (0.0029)	0.1423*** (0.0298)
PC Negative	-1,520.2575*** (117.5832)	-53.2279*** (6.0230)	-1,219.7824*** (112.7468)	-45.6814*** (5.8457)
PC Positive	-361.6102*** (27.8448)	-12.6808*** (1.3715)	-357.7482*** (23.9052)	-11.1068*** (1.1578)
Constant	3,547.3866*** (273.1847)	124.9889*** (14.1257)	2,621.7706*** (487.7878)	360.8531*** (129.9377)
Observations	1,608,958	1,065,735	1,608,958	1,065,735
R-squared	0.6318	0.9383	0.6318	0.9383
Number of wells	17,598	4,685	17,598	4,685
Well FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	No	No
Macro Controls	No	No	Yes	Yes

Dependent variable is the monthly oil production in barrels.

Robust standard errors clustered at the well and month level in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

Table A3.5: FE Models with Logs

VARIABLES	(1) Prod - H	(2) Prod - V	(3) Prod - H	(4) Prod - V
$Ln(Prod_{t-1})$	0.6065*** (0.0022)	0.6291*** (0.0055)	0.6023*** (0.0020)	0.6262*** (0.0051)
$Ln(Prod_{t-2})$	0.0803*** (0.0019)	0.2358*** (0.0052)	0.0803*** (0.0019)	0.2358*** (0.0052)
PC Negative	-0.3619*** (0.0297)	-0.0895*** (0.0051)	-0.3357*** (0.0282)	-0.0567*** (0.0046)
PC Positive	-0.3047*** (0.0251)	-0.0744*** (0.0039)	-0.2801*** (0.0245)	-0.0641*** (0.0033)
Constant	-16.6335*** (1.4821)	-4.5214*** (0.2734)	-10.6930*** (0.7006)	-1.6587*** (0.0854)
Observations	1,608,922	1,065,711	1,608,922	1,065,711
R-squared	0.5180	0.7522	0.5180	0.7522
Number of wells	17,598	4,685	17,598	4,685
Well FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	No	No
Macro Controls	No	No	Yes	Yes

Dependent variable is the natural log of monthly oil production in barrels.
Robust standard errors clustered at the well and month level in parentheses and
*** p<0.01, ** p<0.05, * p<0.1.

Table A3.6: FE Models with IHS

VARIABLES	(1) Prod - H	(2) Prod - V	(3) Prod - H	(4) Prod - V
<i>IHS(Prod_{t-1})</i>	0.6321*** (0.0020)	0.6697*** (0.0057)	0.6321*** (0.0020)	0.6697*** (0.0057)
<i>IHS(Prod_{t-2})</i>	0.0453*** (0.0017)	0.2037*** (0.0054)	0.0453*** (0.0017)	0.2037*** (0.0054)
PC Negative	-0.3172*** (0.0185)	-0.6490*** (0.0312)	-0.30045*** (0.0161)	-0.6186*** (0.0576)
PC Positive	-0.1679*** (0.0098)	-0.3300*** (0.0146)	-0.1422*** (0.0132)	-0.2991*** (0.0989)
Constant	6.9423*** (0.2939)	1.3656*** (0.0340)	10.3786** (4.1864)	1.0106*** (0.0378)
Observations	1,608,958	1,065,735	1,608,958	1,065,735
R-squared	0.5471	0.7833	0.5471	0.7833
Number of wells	17,598	4,685	17,598	4,685
Well FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	No	No
Macro Controls	No	No	Yes	Yes

Dependent variable is the hyperbolic sine transformed monthly oil production in barrels.

Robust standard errors clustered at the well and month level in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

Table A3.7: FD Models with Logs

VARIABLES	(1) Prod - H	(2) Prod - V	(3) Prod - H	(4) Prod - V
$Ln(Prod_{t-1})$	0.4587*** (0.0094)	0.1484*** (0.0229)	0.4560*** (0.0094)	0.1483*** (0.0229)
PC Negative	-0.0048** (0.0021)	-0.0019 (0.0018)	-0.0071*** (0.0021)	-0.0005 (0.0018)
PC Positive	0.0034 (0.0021)	-0.0013 (0.0018)	0.0118*** (0.0022)	-0.0000 (0.0018)
Ln(MSCI)			-1.2485*** (0.0828)	-0.2413*** (0.0561)
Ln(US 10 Year)			0.9809*** (0.0274)	0.7970*** (0.0401)
Ln(USD Index)			-5.4679*** (0.1921)	-1.5186*** (0.1408)
Ln(Copper)			0.3085*** (0.0572)	0.1322*** (0.0351)
Constant	-0.0066*** (0.0005)	-0.0275*** (0.0008)	0.0108*** (0.0009)	-0.0232*** (0.0009)
Observations	1,591,127	1,060,152	1,591,127	1,060,152
Number of wells	17,553	4,679	17,553	4,679
$Prod_{t-2}$ IV	Yes	Yes	Yes	Yes
$Prod_{t-3}$ IV	No	No	No	No
Macro Controls	No	No	Yes	Yes

Dependent variable is the natural log of monthly oil production in barrels.
Robust standard errors clustered at the well and month level in parentheses
and *** p<0.01, ** p<0.05, * p<0.1.

Table A3.8: FD Models with Logs

VARIABLES	(1) Prod - H	(2) Prod - V	(3) Prod - H	(4) Prod - V
$Ln(Prod_{t-1})$	0.4641*** (0.0064)	0.2034*** (0.0154)	0.4637*** (0.0064)	0.2034*** (0.0154)
PC Negative	-0.0048** (0.0021)	-0.0026 (0.0019)	-0.0070*** (0.0021)	-0.0003 (0.0019)
PC Positive	0.0033 (0.0021)	-0.0018 (0.0019)	0.0117*** (0.0022)	-0.0007 (0.0019)
Ln(MSCI)			-1.2528*** (0.0832)	-0.2397*** (0.0578)
Ln(US 10 Year)			0.9759*** (0.0274)	0.7804*** (0.0399)
Ln(USD Index)			-5.4209*** (0.1916)	-1.4075*** (0.1392)
Ln(Copper)			0.3309*** (0.0575)	0.1449*** (0.0363)
Constant	-0.0083*** (0.0004)	-0.0257*** (0.0006)	0.0089*** (0.0009)	-0.0215*** (0.0007)
Observations	1,573,407	1,054,690	1,573,407	1,054,690
Number of api_wellno	17,498	4,663	17,498	4,663
$Prod_{t-2}$ IV	Yes	Yes	Yes	Yes
$Prod_{t-3}$ IV	Yes	Yes	Yes	Yes
Macro Controls	No	No	Yes	Yes

Dependent variable is the natural log of monthly oil production in barrels.
Robust standard errors clustered at the well and month level in parentheses and ***
p<0.01, ** p<0.05, * p<0.1.

Table A3.9: FD Models with IHS

VARIABLES	(1) Prod - H	(2) Prod - V	(3) Prod - H	(4) Prod - V
<i>IHS(Prod_{t-1})</i>	0.6329*** (0.0104)	0.2491*** (0.0284)	0.6299*** (0.0122)	0.2489*** (0.0354)
PC Negative	-0.0241*** (0.0019)	-0.0069*** (0.0016)	-0.0109*** (0.0020)	-0.0036 (0.0025)
PC Positive	0.0134*** (0.0020)	-0.0009 (0.0016)	0.0167*** (0.0022)	-0.0015 (0.0016)
Ln(MSCI)			-0.5595*** (0.0509)	-0.1166*** (0.0281)
Ln(US 10 Year)			0.5761*** (0.0165)	0.3734*** (0.0197)
Ln(USD Index)			-2.9553*** (0.1168)	-0.6496*** (0.0709)
Ln(Copper)			0.0958*** (0.0353)	0.0810*** (0.0174)
Constant	-0.0060*** (0.0003)	-0.0133*** (0.0005)	0.0032*** (0.0005)	-0.0114*** (0.0005)
Observations	1,591,175	1,060,184	1,591,175	1,060,184
Number of wells	17,553	4,679	17,553	4,679
<i>Prod_{t-2}</i> IV	Yes	Yes	Yes	Yes
<i>Prod_{t-3}</i> IV	No	No	No	No
Macro Controls	No	No	Yes	Yes

Dependent variable is the hyperbolic sine transformed monthly oil production in barrels.

Robust standard errors clustered at the well and month level in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

Table A3.10: FD Models with IHS

VARIABLES	(1) Model 3	(2) Model 4	(3) Model 3	(4) Model 4
<i>IHS(Prod_{t-1})</i>	0.5768*** (0.0062)	0.3102*** (0.0171)	0.5658*** (0.0060)	0.3001*** (0.0165)
PC Negative	-0.0230*** (0.0018)	-0.0079*** (0.0016)	-0.0096*** (0.0012)	-0.0048 (0.0461)
PC Positive	0.0119*** (0.0019)	-0.0011 (0.0016)	0.0155*** (0.0023)	-0.0017 (0.0019)
Ln(MSCI)			-0.5949*** (0.0496)	-0.1191*** (0.0290)
Ln(US 10 Year)			0.5799*** (0.0161)	0.3618*** (0.0193)
Ln(USD Index)			-3.0297*** (0.1135)	-0.5741*** (0.0692)
Ln(Copper)			0.1297*** (0.0343)	0.0914*** (0.0180)
Constant	-0.0073*** (0.0003)	-0.0122*** (0.0004)	0.0020*** (0.0005)	-0.0103*** (0.0004)
Observations	1,573,466	1,054,730	1,573,466	1,054,730
Number of wells	17,498	4,663	17,498	4,663
<i>Prod_{t-2}</i> IV	Yes	Yes	Yes	Yes
<i>Prod_{t-3}</i> IV	Yes	Yes	Yes	Yes
Macro Controls	No	No	Yes	Yes

Dependent variable is the hyperbolic sine transformed monthly oil production in barrels.

Robust standard errors clustered at the well and month level in parentheses and *** p<0.01, ** p<0.05, * p<0.1.

A.3 Timeline of Covid-19 related restrictions in Turkey, March-June 2020

March 11: First Covid case in Turkey ¹

March 12: Sports games to be played without audience

March 14: Unilateral ban on flights to and from Germany, France, Spain, Norway, Denmark, Belgium, Austria, Sweden and the Netherlands until April 17

March 16: Schools suspended; congregational prayers suspended; cinemas, concert halls, wedding halls, cafes, bars, night clubs, massage parlors, and gyms closed

March 20: Scientific/cultural/artistic events and conferences suspended

March 21: Lockdown order for people who are 65+ or have chronic diseases; dine-ins at restaurants after midnight banned

March 24: 50% capacity for public transport

March 27: Interprovincial travel restricted

April 3: Lockdown order for people who are 20 or below; masks are mandatory in crowded places such as markets; 15 days ban on travel to and from the 30 metropolitan provinces and Zonguldak

April 11-12: Lockdown for the weekend in the 30 metropolitan provinces and Zonguldak

April 18-19: Lockdown for the weekend in the 30 metropolitan provinces and Zonguldak

April 23-26: Lockdown in the 30 metropolitan provinces and Zonguldak

¹All information in this section is collected from Turkey's Official Gazette

May 1-3: Lockdown in the 30 metropolitan provinces and Zonguldak

May 11: Shopping malls and hairdressers re-opened

May 16-19: Lockdown in 15 provinces (Ankara, Balıkesir, Bursa, Eskisehir, Gaziantep, Istanbul, Izmir, Kayseri, Kocaeli, Konya, Manisa, Sakarya, Samsun, Van and Zonguldak)

Until May 23: Lockdown during weekends in the 30 metropolitan provinces and Zonguldak

May 23-26: National lockdown during Eid

May 29: Congregational prayers restart

June 1: Cafes, restaurants, gyms re-open but no service after 10pm; interprovincial travel restrictions lifted

June 3: Lockdown order for 65+ lifted

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