ABSTRACT

ROH, HYEONGYUL. Three Essays on Energy, Environmental, and Resource Economics (Under the direction of Dr. Harrison Fell).

This dissertation comprises three essays in the areas of energy, environmental, and resource economics. The first essay examines the impact of recent dramatic increases in renewable generation on a systematic forward price premium (persistently positive forward minus spot prices, FPP) and firms’ intertemporal production decisions. Specifically, first, I develop a theory model of imperfect competition to show how increased wind generation can increase the FPP. Next, I implement a novel empirical approach using machine learning methods to predict the impact of wind generation on the FPP and strategic generation behaviors of conventional generators. Consistent with the theoretical prediction, I empirically find that increased wind generation increases the FPP. Also consistent with the theory model, I find dominant firms withhold supply in the forward market to engage in intertemporal price discrimination as wind generation increases. In contrast, fringe producers respond to the FPP increases by increasing supply in the forward market to exploit the price differentials. The results point to the challenges in achieving market efficiency with increased wind generation in the presence of market power. Furthermore, the variety of ways, in which the other factors accompanied by wind generation—forecast uncertainty and wind generation variability—affect market outcomes, highlight the importance of extensive consideration when assessing the costs of renewable generation.

The second essay builds on prior bioeconomic models of evolving pest and pathogen resistance to biocides (e.g., pesticides and antibiotics) to investigate the adaptive management (AM) of resistance, with uncertainty in parameters governing renewability of pesticide susceptibility. The biological model is a multi-dimensional Markov process in a continuous state space admitting conjugate priors in Bayesian belief-updating. We show how to improve efficiency of Bayesian inference by optimally weighting information from each state variable using the correlation between the states. In an application to transgenic Bacillus thuringiensis
(Bt) corn to control European corn borer, we find that the expected value of perfect information (EVPI) about renewability of susceptibility decreases with accumulating resistance, whereas the value of information (VOI) from AM (bounded above by the EVPI) increases. Contrasting with other AM applications, ‘active’ AM that optimally probes for information yields significantly greater VOI than ‘passive’ AM with high resistance.

The final essay presents a case study that analyzes the impacts of transmission expansion projects in the Texas wholesale electricity market by considering its interaction with recent dramatic increase in wind generation. The $6.9 billion portfolio aims to transmit wind power from remote parts of Texas (primarily west Texas) to more heavily populated areas. To investigate a complex, grid-based electricity market system, this study utilizes a clustering method in machine learning to reduce the size of data dimensions while retaining valuable information. The clustering method classified diverse market conditions into eight categories. Overall, I show that the transmission expansion significantly decreased nodal price discrepancies by efficiently integrating supply and demand throughout the market. Specifically, the expansion facilitated wind generation exports at high wind generation levels and imports at low wind generation levels. However, market-wide analysis revealed that the integrated market was 25% more likely to cause price spikes in Houston as impacts from intermittent wind generation in west Texas spread to other regions. Furthermore, extreme wind generation values (whether high or low) could still exacerbate ERCOT market conditions, which may worsen with planned 63% increase in wind generation units by 2020.
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Three Essays on Energy, Environmental, and Resource Economics

by
Hyeongyul Roh

A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Economics

Raleigh, North Carolina

2018

APPROVED BY:

Dr. Harrison Fell
Committee Chair

Dr. Zachary Brown

Dr. Robert Hammond

Dr. Denis Pelletier
DEDICATION

To Younjee, Ryan and Jason for being my companions.
BIOGRAPHY

Hyeongyul is originally from Seoul, South Korea, where he received a Bachelor of Arts degree in Economics. After graduation, Hyeongyul worked for three years in financial services industry in Seoul and moved to U.S. to pursue a Master of Science degree in Mathematical Finance at Boston University. He then moved to Raleigh and began his Ph.D. in Economics at North Carolina State University where he found his desire for a new career path in energy, environmental, and resource economics. His current research interests lie at the intersection of energy markets and new data analytic tools. He will continue research in energy and environmental economics as a CLIR postdoctoral fellow at the Duke University Energy Initiative.
ACKNOWLEDGMENTS

I especially thank the chair of my committee, Harrison Fell, for his tireless efforts and tremendous investment of time in guiding me through the dissertation. His insightful advice and high expectation of my work were invaluable during this process and will stay with me as I move forward in my academic career. I also have been extremely fortunate to have had the opportunity to work with Zachary Brown. His expertise in mathematical modeling and interdisciplinary research interests were instrumental in expanding my knowledge. I would also like to extend my gratitude to other committee members: Robert Hammond and Denis Pelletier. Their teaching and comments on my work improved the quality of this dissertation and enhanced my appreciation of academic research. Finally, I am grateful to North Carolina State’s Economics Department for financial support through assistantships. I also would like to thank the Jenkins family for their financial backing of a fellowship that supported my final year of dissertation research.
Chapter 1: Wind Generation, Inefficiency, and Market Power in Electricity Markets:
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Chapter 1

Wind Generation, Inefficiency, and Market Power in Electricity Markets: Counterfactual Prediction with Dynamic Neural Networks for Causal Inference

1.1. Introduction

Renewable energy generation in the U.S. has increased dramatically in response to declining production costs, policies favoring renewable energy, and concerns over carbon emissions from fossil fuel generators. However, the integration of wind generation into an electricity market involves numerous challenges. First, given that large-scale energy storage is lacking in most areas, the intermittency driven by weather variation has the potential to adversely affect the market by increasing production variability and forecast uncertainty. Specifically, the rising variability driven by fluctuating wind output causes more frequent ramping of conventional generators and creates price spikes. In addition, the uncertainty driven by the limited predictability of wind complicates the production planning of system operators and requires more back-up capacity to ensure system reliability. Second, even without regard to production variability and forecast uncertainty, the supply increase from the (almost) zero marginal cost
wind generators would affect the strategies that dominant firms use to maximize profits. The behavioral changes of dominant firms would greatly impact market prices and system reliability in the context of inelastic electricity demand. However, although many studies have estimated environmental benefits to be derived from renewable energy (Cullen (2013), Novan (2015), and Fell and Kaffine (2018)), relatively few studies have investigated the changes in the market outcomes caused by large-scale renewable energy generation.

In this paper, I develop a method to quantify the market inefficiency associated with wind generation in the Texas wholesale electricity market (Electric Reliability Council of Texas, ERCOT). First, I develop a theoretical framework of imperfect competition to examine how the integration of wind generation affects the concentrated electricity market and creates market inefficiency. Second, I implement an empirical approach for a more detailed picture of market outcomes by taking advantage of two recent advances: the proliferation of high-frequency data in the electricity market and the development of machine learning methods in economics. Specifically, I employ 256 distinct independent variables to predict load weighted market prices and firm-level generation decisions in sequential markets.¹

Given that growing reliance on intermittent generation has significant impacts on electricity market, two important questions arise with the research tasks: (1) What metrics can be used to reflect the market efficiency in the context of the electricity market? and (2) What specific factors accompanied by wind generation would affect those metrics? To tackle the first problem, I use a forward price premium (persistently positive forward minus spot market prices, FPP) and firms’ intertemporal production decisions to measure the changes in market efficiency. As in most commodities markets, wholesale electricity markets are organized as sequential markets, which comprise a forward market that schedules production a day in advance and a spot market that balances demand and supply. Forward prices should equal the expected spot prices in

¹ I estimate several dependent variables that comprise load weighted prices and firm-level output decisions. To find prediction functions using the machine learning method for the dependent variables, I use the 24-hour lagged values of 256 independent variables and a dependent variable. Therefore, the total number of right-hand side variables used for the estimations is actually in the thousands. Section 3.4 explains the details.
a stylized setting with certain conditions, because both markets trade the same commodity. However, persistent price differences have been documented in most electricity markets. With the positive FPP, consumers (retailers in the wholesale market) are worse off because they pay higher prices to secure their purchases in advance through the forward market. Previous studies provide several potential channels that explain why prices in sequential markets do not converge, such as risk aversion, market power, and artificial congestion manipulated by financial traders. In this paper, however, I investigate how increased wind generation in the presence of market power affects the FPP and firms’ production decisions in sequential markets. More generally, this question is analogous to assessing how price-discriminating firms would change their strategic behaviors in the sequential market in response to exogenous residual demand shifts.

Figure 1.1-1 provides the rationale behind systematic FPP driven by the intertemporal price discrimination of a residual monopolist. A residual monopolist decides how much to sell in each of sequential markets. Whereas demand is inelastically planned for, the monopolist faces downward-sloping residual demand in both forward and spot markets because there exist fringe firms who offer production at their upward-sloping marginal cost curve. In the first market, the monopolist optimally offers $q_1$ by considering his marginal revenue ($MR_1$) and the spot market price ($p_2$), which is an opportunity cost of selling products in the forward market. In the second market, the monopolist has an incentive to sell additional quantity, $(q_2 - q_1)$, because the lower price in the second market does not affect the price charged in the first market. Therefore, the monopolist splits its sales between two markets to maximize the profits by backward induction and creates a consistent price premium. In this paper, theoretical predictions with more generalized settings of slopes indicate that a price premium in the first market can arise when

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2 A simple economic theory assumes the conditions of perfect competition, risk neutrality, and zero transaction costs for no forward price premium. However, the consistent price differentials have been documented in other electricity markets within the context of imperfect competition, such as in California (Borenstein et al. (2008) and in the Iberian market (Ito and Reguant (2016). Further, the systematic positive forward premium in the presence of financial speculators has also been recently documented in the California market (Jha and Wolak, 2014) and Midwest electricity market (Birge et al., 2017). As in most commodity markets, deregulated electricity markets allow the participation of purely financial traders because they are expected to help eliminate predictable pricing gaps between the forward and spot markets by introducing liquidity and by enhancing informational efficiency. However, a positive FPP has persisted despite the presence of financial speculators in the ERCOT as in other markets.
integrating wind generation into the sequential markets in the presence of market power.

Second, to examine what specific factors accompanied by wind generation affect FPP, I define and quantify the implication of wind generation by decomposing the generation into three main factors to reveal how the specific factors incorporated in wind generation affect the metrics of efficiency: an increase in production variability, an increase in forecast uncertainty, and an aggregate production increase. The variability denotes the manner in which wind outputs fluctuate within a certain time frame and is defined by hourly wind variances at 15-minute intervals of wind generation. The uncertainty defines how difficult it is to predict the actual outputs of wind generation and is measured by the difference between wind generation forecasts made in the forward market and the realized quantities attained in the spot market. Increasing aggregate wind generation simply denotes increases in realized hourly generation (the sum of 15-minute intervals of wind generation) with fixed levels of the variance and forecast error.

Thereafter, I examine how those three factors influence the FPP and firms’ behaviors. Specifically, I employ high frequency data that contain detailed market conditions and leverage a novel empirical approach using dynamic neural networks to measure the causal effects of wind generation on market outcomes based on counterfactual predictions. The predictions made through the machine learning method construct time series data for hourly clearing prices and cleared quantities in the forward and spot markets. These counterfactual paths describe what would have happened to energy prices and supplies at each transmission node if there had been either low or high wind generation. Furthermore, I consider the difference between the counterfactual paths to estimate the heterogeneous treatment effects of the wind generation increase on the market prices and quantities across different firms in certain hours and seasons. Finally, I characterize the impacts by decomposing wind generation increases into the three components mentioned.

The empirical results indicate that changes in the three components driven by increased wind generation have heterogeneous channels through which to affect market outcomes. Most importantly, consistent with the theoretical predictions, I empirically find that wind generation
with fixed variability and uncertainty increases FPP and incites heterogeneous firms’ responses. I demonstrate that dominant firms maintain their strategy of engaging in intertemporal price discrimination even when there is a significant increase in wind generation, whereas fringe producers exploit price differentials in the sequential markets. Also consistent with the theory model, I find the FPP spikes during transition hours when wind generation is either gradually decreasing or increasing because there is more inelastic residual demand for conventional generators in the real-time market. Second, the increased production uncertainties of the spot market driven by wind forecast errors cause FPP to increase because the demand shifts to the forward market. Third, the increased the production variability creates more frequent price spikes in the spot market and induces a slight decrease in the FPP.

The results present the challenges in achieving market efficiency with increased wind generation when the market is subject to the exercise of market power. Even in the absence of main adverse factors, such as production variability and forecast uncertainty, wind generation creates the systematic FPP and causes market inefficiency because firms exert more market power in the forward market and engage in intertemporal price discrimination with the changes. Furthermore, the variety of ways, in which the other factors accompanied by wind generation—forecast uncertainty and wind generation variability—affect market outcomes, highlight the importance of taking a wide variety of factors into consideration when assessing the social costs of renewable generation.

This paper is related to several themes found in the existing literature. First, it builds on an extensive body of literature that examines systematic price differences in sequential markets in the context of a risk premium, market power, limited opportunities to arbitrage, and artificial congestion manipulated by financial traders. For example, Borenstein et al. (2008) present both data and documentary evidence that a form of monopsony power over forward and spot markets

3 Bessembinder and Lemmon (2002), Longstaff and Wang (2004), and McAfee and Vincent (1993) indicate that risk premium can explain systematic forward premium. Jha and Wolak (2014) explain the premium by transaction costs. Birge et al. (2017) find evidence that financial players introduce artificial congestion to the system to make larger profits from financial options.
can explain a consistent negative FPP in the California electricity market. Ito and Reguant (2016) demonstrate how monopoly power in the Iberian market can generate a systematic positive FPP as dominant firms endogenously withhold their sales in the forward market. Furthermore, they extend the discussion to the role of financial players, which also has been recently documented by several studies (Mercadal (2016) and Birge et al. (2017)). When a positive FPP exists, an arbitrageur may sell a quantity in the first market and trade it back in the spot market to exploit price differences. The arbitrage by financial speculators attenuates market power in the forward market due to increased competition in supplies. However, generators still have market power in the spot market because financial traders, without generating resources, cannot increase electricity production in the second market. Ito and Reguant (2016) and Mercadal (2016) demonstrate that conventional generators indeed exert more market power in the spot market when there is more arbitrage, which results in increased costs because demand is served by more expensive generators.4

While these studies are informative, I demonstrate that recent dramatic changes in wind generation have become an additional driver to address systematic price differentials under imperfect competition and, yet, have idiosyncratic impacts for several reasons. First, wind generation decreases the residual demand of dominant firms in both the forward and spot markets by exogenous weather variations and makes the markets more competitive; however, unlike arbitrage, it does not involve a trading back in the spot market. In other words, it induces the changes in strategic behaviors of firms and the FPP; however, it does not cause “the balloon effect” in the spot market as in arbitrage.5 Second, in contrast to conventional fossil fuel fleets, wind generation units have zero marginal cost and are nondispatchable. Thus, the integration of wind generation into the market causes an exogenous shift in the residual demand curve, rather

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4 Ito and Reguant (2016) and Mercadal (2016) also demonstrate that price convergence in itself is not a sufficient statistic for market efficiency because inefficiencies from market power remain even with the reduced pricing gaps.

5 When a latex balloon is squeezed, air is moved, but does not disappear, instead moving into another area of less resistance. When financial traders exist, the market power exerted by the dominant firms does not disappear, but rather moves away from the forward to the spot market. Wind generation, however, exogenously increases electricity production and actually decreases the residual demand for dominant firms in the spot market.
than a change of slope as is observed with market entrants with conventional generators. Third, as wind generation is generously supported by federal and state policies, wind generators are able to submit their bids with negative prices in the forward market.\(^6\)

In addition, this paper is related to a recent study that quantifies the economic value of intermittent renewable energy generation (Gowrisankaran et al., 2016). Unlike in the canonical model, however, the market in this paper is not assumed to be competitive, and I focus on firms’ intertemporal price discrimination between the sequential markets.

Second, this study makes a methodological contribution by deploying dynamic neural networks to replicate industrial dynamics and predict market outcomes based on several counterfactuals for causal inferences. Recently, machine learning methods have provided important new tools to improve the estimation of causal effects in high-dimensional settings because in many cases it is important to flexibly control for a large number of covariates as a part of an estimation strategy for drawing causal inference from the data.\(^7\) In this paper, comparing the machine learning method approach with a conventional panel regression method provides two primary findings. First, the machine learning method can find accurate prediction models of heterogeneous energy market outcomes, which, for example, are made of several time fixed effects. Dynamic neural networks outperform the panel regression in the mean square error (MSE) of the out-of-sample forecasts. In particular, neural networks can predict the timings of

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\(^6\) The Production tax credit (PTC) has been used since 1992 to stimulate investment in some renewable energy technologies, including wind. It was most recently renewed in December 2015 and extended through 2019. As of 2016, the PTC for wind was $0.023/kWh (equivalently, $23/MWh), but it will decline in 2017. Senate Bill 7 (1999) in Texas requires retail electric providers to buy renewable energy. Senate Bill 20 (2005) in Texas mandates transmission access improvement in response to rapid growth in wind generation.

\(^7\) Athey and Imbens (2017), Mullainathan and Spiess (2017), and Varian (2014) have provided useful overviews about machine learning for causal inference. Athey and Imbens (2015) used random forests to estimate heterogeneous effects in randomized trials while minimizing concerns about “cherry picking.” Bajari et al. (2015) reviewed and applied several popular methods from machine learning literature to the problem of demand estimation. Burlig et al. (2017) generated counterfactual time paths for control groups for a causal inference. Chernozhukov et al. (2016) used the “double selection” approach with LASSO to both predict selection into treatment as well as to predict an outcome. Hartford et al. (2016) proposed a recipe for artificial economic intelligence that incorporates econometric theory (IV) into deep neural networks. Such research is a source of important potential for the future studies on a variety of topics that are of interest to applied microeconomists. Deep neural nets, such as dynamic neural networks, can be extended to the instrumental variable (IV) framework because that framework employs a number of layers that consist of a set of neurons.
extreme events such as price spikes, which frequently occur in the electricity market and significantly affect market outcomes. Second, using dynamic neural networks, one does not need to specify modeling assumptions (like those about functional forms on covariates), which may improve the credibility of policy analysis based on predictions. Specifically, this approach is beneficial for studies performed in the context of the electricity wholesale market because, although electricity prices and generation can change for various reasons, it is difficult to correctly specify all the relations (either linear or nonlinear) based on hand-curating functional forms. Given that the proliferation of high-frequency data is available in the electricity market, we can simply let the data tell us which functional form works best.

The rest of this paper is organized as follows. The next section describes theoretical models used to outline ways in which wind generation interacts with an FPP under imperfect competition. Section 1.3 gives institutional details and describes the dataset used for empirical analysis. Section 1.4 introduces machine learning methods and addresses the details of empirical strategies. Section 1.5 presents the results. Section 6 concludes the paper.

1.2. Model

Most wholesale electricity markets in the U.S. are organized as sequential markets. In this section, I describe a theoretical model indicating how a residual monopolist decides production in the sequential markets and how those production decisions would create a systematic positive FPP. I employ a model developed by Ito and Reguant (2016) and modify the theoretical framework to reflect idiosyncratic market conditions in the ERCOT and the impacts of current asymmetric wind generation on the sequential markets.

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8 The price spikes are defined as being ten-times greater than the mean value of prices just for a simple notation; thus, price spikes are the prices approximately greater than $300MWh.
9 High-frequency data, however, may involve overfitting. Complementary tools embedded in machine learning methods can attenuate the overfitting (see Appendix for more details).
10 The process of scheduling supplies in advance is considered to improve the efficiency of the final allocation of electricity supplies that have uncertainty in their prices and quantities. In the oligopolistic setting, sequential markets can help reduce the extent of market power (Allaz and Vila, 1993).
1.2.1. Baseline Model

For the baseline model, I simply assume that fringe suppliers are bidding at their marginal cost and that there exists a residual monopolist to engage in intertemporal price discrimination in the sequential markets. The problem of the monopolist is to decide how much to sell in the first market (forward or day-ahead market) at a price $p_{DA}$ and how much to actually commit in the second market (spot or real-time market) at a price $p_{RT}$. Final production is determined by the sum of commitments in each market.

The residual demand in the day-ahead market is defined by

$$D_{DA}(P_{DA}) = A - b_{DA}P_{DA} \tag{1.1}$$

This equation reflects the forecasted total demand $A$ and the slope of the marginal cost curve of fringe firms $b_{DA}$. The logic of this demand function is that the residual demand is determined by perfectly inelastic demand $A$ minus the willingness to produce by fringe suppliers, who are willing to produce as long as the market price $P_{DA}$ is greater than their marginal cost $C^{small}(q) = q / b_{DA}$.

In the real-time market, the total demand remains $A$ minus the quantity sold in the first market $q_{DA}$, and both a residual monopolist and fringe firms can update their commitments to produce as follows:

$$D_{RT}(q_{DA}, P_{RT}) = A - q_{DA} - b_{RT}P_{RT} \tag{1.2}$$

For the special case of $b_{DA} = b_{RT}$, the residual demand reflects that fringe suppliers are willing to supply electricity along with their original supply curve (Figure 1.1-1). In the context of the electricity market, Ito and Reguant (2016) found that $b_{DA} \geq b_{RT}$ because production tends to be less flexible in the real-time market. Hortaçsu and Puller (2008) found evidence that the supply curve of fringe firms is relatively inelastic in real-time markets because of a lack of sophistication or adjustment and participation costs. In this paper, I do not impose this condition when solving the equations, but I do investigate how it changes the comparative statics for equilibrium with wind generation.
The monopolist maximizes profits by backward induction. In the second market, \( p_{DA} \) and \( q_{DA} \) have already been determined. Thus, the monopolist’s problem in the second market is

\[
\begin{align*}
\max_{q_{RT}} & \quad p_{RT} q_{RT} - C(q_{DA} + q_{RT}) \\
\text{s.t.} & \quad D_{RT}(q_{DA}, p_{RT})
\end{align*}
\] (1.3)

The solution to equation (1.3) gives an implicit solution for \( p_{RT} \) and \( q_{RT} \) with respect to \( q_{DA} \). In the day-ahead market, the monopolist considers both periods and \( p_{RT} \) and \( q_{RT} \) becomes a function of \( q_{DA} \) as follows:

\[
\begin{align*}
\max_{q_{DA}} & \quad p_{DA} q_{DA} + p_{RT}(q_{DA}) q_{RT}(q_{DA}) - C(q_{DA} + q_{RT}(q_{DA})) \\
\text{s.t.} & \quad D_{DA}(p_{DA})
\end{align*}
\] (1.4)

With a simple linear residual demand and a constant marginal cost function \( C(q) = cq \), I determine an FPP at market equilibrium and summarize some intuitive comparative statics in equilibrium.\(^{11}\)

\[
FP\ P^* = \frac{2Ab_{RT} - Ab_{DA} - b_{DA} b_{RT} C}{b_{DA}(4b_{RT} - b_{DA})}
\] (1.5)

I assume that the monopolist is a net seller in both the day-ahead and real-time markets, which is consistent with the ERCOT data. This model indicates that once there exist a positive FPP, a monopolist becomes a net seller in the day-ahead market \((q_{DA}^* > 0)\) and vice versa. If I impose the opposite assumption (i.e., the FPP is a negative value), then a dominant firm becomes a net buyer (a monopsonist).

Several important properties are derived from the solutions. First, an FPP is increasing in total demand \( A \), decreasing in \( b_{DA} \), increasing in \( b_{RT} \), and decreasing in marginal cost \( C \). The total demand \( A \) has a positive relation with the FPP. In other words, during peak demand hours, the FPP is likely to increase. The extent of the changes, however, also depends on the slope of the residual demand, as shown in equation (1.5). For example, if residual demand for the day-

\(^{11}\) The appendix contains all other solutions, such as clearing prices and cleared quantities in the day-ahead and real-time markets at equilibrium.
ahead market is more elastic, the FPP would decrease. On the other hand, if residual demand for the real-time market is more elastic, the FPP would increase. In addition, $b_{DA}$ and $b_{RT}$ are important determinants of the firm’s supply decisions. When $b_{DA}$ is greater than $b_{RT}$, a monopolist sells more in the real-time markets than in the day-ahead markets ($q_{DA} < q_{RT}$). With the special case $b_{DA} = b_{RT}, q_{DA} = q_{RT}$.

### 1.2.2. Model with Wind Generators

I integrate wind generation into the structural model, as mentioned in the previous section. To do so, I consider several distinctive features of wind generation. First, the strategies of wind generators in the ERCOT, with their asymmetric firm size, show neither endogenous withholding nor arbitrage. Instead, in the day-ahead market, they submit almost the same supply bids for a small portion of their capacity with all negative prices. Despite an 83% increase in installed wind capacity in the ERCOT from 2011 to 2015, the cleared quantities for wind generation in the day-ahead market are almost the same (Figure 1.3). Additionally, the final committed wind generation in the real-time market is mainly determined by exogenous weather patterns (e.g., wind speed and direction). Thus, a theoretical model in this section assumes that wind generation decisions in the sequential market have been exogenously determined.\(^\text{12}\) Second, almost all the wind turbines in the ERCOT are owned by firms without any fossil fuel units; thus, the dominant firms do not endogenously consider wind generation when they maximize profits. Third, in contrast to dispatchable fossil fuel units, wind generation units have zero marginal cost and are nondispatchable. Thus, the integration of wind generation shifts the exogenous residual demand curve rather than changing the slope of the supply curve, which is usually driven by cases in which additional conventional generators enter the market.

\(^\text{12}\) This is also a common assumption in the context of electricity markets (Cullen (2013), Gowrisankaran et al. (2016), and Novan (2015)).
Incorporating all these factors, the modified residual demand is defined by

\[ D_{DA}(P_{DA}) = A - w_{DA} - b_{DA}P_{DA} \quad (1.6) \]

\[ D_{RT}(q_{DA}, P_{RT}) = A - q_{DA} - w_{DA} - w_{RT} - b_{RT}P_{RT} \quad (1.7) \]

Residual demand in sequential markets is decreased by the integration of wind generation in which \( w_{DA} \) denotes the amount of wind generation sold in the day-ahead market, and \( w_{RT} \) denotes the amount sold in the real-time market. Figures 1.1-2 provide a graphical illustration of the changes in production strategies of a residual monopolist driven by integrating wind generation into sequential markets. An upper panel in the Figure 1.1-2 shows the residual demand shift by \( w_{DA} \), while bottom panel shows the shift of residual demand by \( w_{RT} \). An FPP with the new residual demands are

\[ FPP^* = \frac{2Ab_{RT} - A b_{DA} - b_{DA} b_{RT} C + b_{DA} w_{DA} - 2 b_{RT} w_{DA} + b_{DA} w_{RT}}{b_{DA} (4b_{RT} - b_{DA})} \quad (1.8) \]

We find some useful comparative statics. First, as in the baseline model, if a monopolist is a net seller in the day-ahead market \( (q_{DA}^* > 0) \), there exists a positive FPP and vice versa. With a negative FPP, a dominant firm becomes a net buyer. Second, the FPP is increasing in \( A \), decreasing in \( w_{DA} \), and increasing in \( w_{RT} \). Finally, with an increase in wind generation either through the day-ahead \( (w_{DA}) \) or real-time market \( (w_{RT}) \), the FPP is increasing in \( b_{DA} \) and decreasing in \( b_{RT} \) because \( \frac{\partial^2 FPP}{\partial w_{DA} \partial b_{DA}} \) and \( \frac{\partial^2 FPP}{\partial w_{RT} \partial b_{DA}} > 0 \) and \( \frac{\partial^2 FPP}{\partial w_{DA} \partial b_{RT}} \) and \( \frac{\partial^2 FPP}{\partial w_{RT} \partial b_{RT}} < 0 \). In other words, when wind generation is increased, the FPP increases when residual demand in the day-ahead market is more elastic, whereas the FPP decreases when residual demand in the real-time market is more elastic.

Under this simple theoretical framework, we can predict that an increase in wind generation would increase an FPP because \( w_{RT} \) is much larger than \( w_{DA} \) in the ERCOT. Table 1.2 and Figure 1.3 clearly indicate that only 5% of the realized total wind generation \( (w_{DA} + w_{RT} \) in this model) is sold through the day-ahead market. Table 1.1, Figure 1.2-1, and Figure 1.2-2 show that the means and quartiles of the FPP during 2011 and 2016 in the ERCOT were consistently positive.
Specifically, theoretical models indicate that the extent of an FPP under imperfect competition can be affected by a combination of total demand, the slope of residual demands, and wind generation. These predictions are consistent with the data in Figure 1.2-1, which indicates that the FPP has some spikes during the peak demand hours such as 7 a.m. and 4–7 p.m. The extent of these changes, however, also depends on the slope of residual demand, as shown in Figure 1.2-2. When the market demand rapidly increases without enough generators online (e.g., 7 a.m. in low net load months), and thus the residual demand more inelastic, the FPP spikes upward. The degree of this upward spikes is greater than that for the same hour during high net load months because the residual demand during high net load months is likely to be more elastic, because there are relatively high demands throughout the day and night so that more generators are online.\textsuperscript{13}

1.2.3. Production Decisions under Volatility and Uncertainty and Compounding Factors

The theoretical models in the previous section clearly reflect the strategic decisions of a residual monopolist, incentives to withhold in the day-ahead market, and the rationale behind the existence of systematic FPP. Based on the model, wind generation might increase the FPP. However, because \( w_{DA} \) and \( w_{RT} \) are the realized outcomes, the model does not include other important factors incorporated in wind generation: an increase in both wind volatility and forecast uncertainty. The production decisions under exogenous volatility should be quite different if we consider the dynamic constraints of fossil fuel units (Appendix B2). In addition, according to economic theory, decisions under uncertainty are always different from the solutions to a static problem.

The theoretical model also might not consider the possible interactions between wind generation and the slope of residual demand. For example, it is a plausible extension of the theoretical model to reflect that \( b_{RT} \) is a function of \( w_{DA} \) and \( w_{RT} \) rather than a constant. Even

\textsuperscript{13} During shoulder months, some baseload generators and wind generators can satisfy the entire market demand during nighttime and all other generators would be offline during the time period.
with the same volatility within an hour and the same uncertainty, some transition hours—when
wind either gradually decreases or increases—may entail additional start-up costs and may
increase the marginal costs of fringe firms because some of their generators are likely to be
offline during that time.

Thus, it is challenging and computationally infeasible to solve a theoretical model that
includes all the characteristics of the market interactions. Instead, in Section 1.4, I propose a
more sophisticated prediction tool to test the theoretical results and characterize the industrial
dynamics in a data-driven manner. The main investigations such as heterogeneous wind impacts
on an FPP, firms’ quantity responses, and other related market outcomes over seasons and hours
are conducted by the machine learning method addressed in Section 1.4.

1.3. Context and Data

As a deregulated electricity market, the ERCOT manages the flow of electric power to 24 million
Texas customers, which represents approximately 90% of the state’s electric load (ERCOT,
2016). Texas uses the most electricity per capita in the U.S. The ERCOT has 570 generation
units, including fossil fuel fleets, wind, and nuclear, which are owned by approximately 70 firms.
Conventional fossil-fueled generators are owned by 40 firms.

The ERCOT grid is an electrical island because the ERCOT is not synchronously
connected to its neighboring grid systems. The only connection between the ERCOT grid and
neighboring electrical systems is via direct current ties, but the amounts traded are quite small
(ERCOT, 2010). Electricity generation and retailing are deregulated, whereas the transmission
and distribution of energy remains regulated to ensure that competitors in the generation and
retailing markets have open access to buy and sell power (Cullen, 2015).

In 2016, total generation capacity in the ERCOT comprised 52% natural gas power
plants, 22% coal, 20% wind, 6% nuclear, and 1% others, which represents a larger share of
natural gas power plants compared with many other markets. Actual energy use in 2016 was
somewhat different from the total generation capacity: 43.7% natural gas, 28.8% coal, 15.1% wind, 12% nuclear, and 0.5% others. From 2011 to 2016, installed wind capacity increased by approximately 90% and monthly average natural gas price fluctuated between $1.91 and $6.54 per thousand cubic feet.

1.3.1. Sequential Market

The ERCOT has a sequential market comprising the day-ahead and real-time markets. Each firm sells its energy to buyers through a multi-unit complementary bidding mechanism in both markets. The day-ahead operations schedule production for the 24 hours of the next day. It is a financial market ensuring the reliability of the transmission grid. In the day-ahead market, qualified scheduling entities (QSEs) representing firms submit bids to sell and/or to buy electricity, and they also submit bids to supply capacity for reserve market (ancillary services, AS) by 10 a.m. AS is competitively procured by the ERCOT to ensure the availability of generation capacity to provide enough energy to maintain the electric system within allowable reliability limits. Given that the AS prices are opportunity costs of selling energy in the day-ahead market, AS prices and quantities are related to other market outcomes (Figure 1.2-3). The ERCOT clears the day-ahead market at 1:30 p.m.

Using offers from individual resources while considering conditions on the transmission network, the ERCOT controls the real-time market by running a security-constrained economic dispatch (SCED) at least every 5 minutes. The SCED determines the most economical dispatch of individual resources across the grid.

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14 Appendix B3 presents the details on the ways in which firms bid in the day-ahead and real-time market.
15 The primary ancillary services are up regulation, down regulation, responsive reserves, and nonspinning reserves. In general, the purpose of responsive and nonspinning reserves is to protect the system against unforeseen contingencies (e.g., unplanned generator outages, load forecast error, wind forecast error) rather than to meet normal load fluctuations. The ERCOT procures responsive reserves to ensure that the system frequency can be quickly restored to appropriate levels after a sudden, unplanned outage of generation capacity. Nonspinning reserves are provided from slower responding generation capacity and can be deployed alone to restore responsive reserve capacity. Regulation reserves are capacity that responds every four seconds, either increasing or decreasing as necessary to fill the gap between energy deployments and the actual system load.
The rationale behind sequential markets is simple. First, generation is much cheaper when it is planned; thus, scheduling forecasted demand in advance decreases production costs. Specifically, baseload generators with lower marginal costs generally have high startup costs and cannot adjust the level of production promptly. However, generators called “peakers” can start and vary the production level quickly although they have higher marginal costs. By scheduling production in the day-ahead market, it is easier to satisfy expected demand with cheaper generators and only respond to unexpected demand changes with peakers. In addition, scheduling the next-day supplies in the day-ahead market increases efficiency by considering the additional startup costs included in the complementary bidding (Appendix B3). Second, the existence of the forward market also makes consumers better off because they can face less risk in the forward market. Price is usually more volatile in the real-time market (see Table 1.1). Finally, a sequential market can enhance competition among firms if they are in an oligopolistic market (Allaz and Vila, 1993).

Even if it would be efficient to schedule generation in the day-ahead market as mentioned, market participants are not always incentivized to do so. In the ERCOT, the volume of day-ahead purchases provided through a combination of generator-specific and virtual energy offers has been approximately 50% of the real-time load from 2011 to 2016 (Potomac Economics, 2015).

1.3.2. Forward Price Premium and Market Power

Systematic price differences in a sequential market have been observed in many wholesale electricity markets, including the ERCOT. Moreover, a positive FPP persisted despite the presence of virtual traders in the ERCOT. The systematic FPP can arise from the market power

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16 Usually, baseload generators are combined-cycle generators using natural gas and coal generators among fossil fuel units that can be dispatched. However, simple-cycle natural gas generators that are classified to “peakers” use a jet engine and quickly reach their full capacity while having higher marginal costs.

17 The systematic forward price premium has been documented in the California market (Jha and Wolak (2014) and Borenstein et al. (2008)), the Iberian Market (Ito and Reguant (2016)), and the Midwest market (MISO) (Birge et al. (2017) and Mercadal (2016)).
on the supply side. Generators with market power have an incentive to exert intertemporal price discrimination by withholding products in the day-ahead market. As they participate in both forward and spot markets, expected real-time market prices can be opportunity costs for those generators to sell the products in the day-ahead market. They will withhold a certain quantity to set marginal prices in the day-ahead market that are higher than the expected prices in the real-time market. After selling that quantity in the first market, a generator has an incentive to sell additional quantity in the second market because the lower price in the second market will not affect the price charged in the first market. Based on this strategy, the generator splits its sales between the forward and spot markets (Coase, 1972). The behavior of generators in the ERCOT is consistent with these strategies.

Previous studies have found that generators have market power in a deregulated electricity market (Borenstein et al. (2008) and Ito and Reguant (2016)). Puller (2007) examined the California market and concluded that generators’ conduct is consistent with Cournot competition. While these studies have found evidence of market power in the zonal market, where prices are allowed to differ, the recent transition to a nodal market structure in electricity markets, including the ERCOT, provides even more opportunities for firms to exert market power.\(^\text{18}\) In the nodal market, there may be a different clearing price in each location or node where electricity is generated or demanded. This price represents the marginal cost of supplying electricity at that node, which varies significantly because nodes are connected by transmission lines with limited capacity. Mercadal (2016) revealed that the Midwest electricity market under a nodal market platform is split into multiple local markets in which concentration is higher and firms have more market power due to the limited capacity of the transmission lines that transport electricity.

\(^{18}\) Appendix B1 provides some more institutional details on the nodal market in the ERCOT.
1.3.2.1. Market Participants in the ERCOT

In this paper, I investigate the strategies of dispatchable units (coal and natural gas) with increased wind generation. The market share of fossil fuel power plants owned by the three biggest firms (Luminant, Calpine, and NRG) is approximately 35% of the total energy demand in the ERCOT, on average (Table 1.2 and Figure D2 in Appendix), depending on the time of day, season, fuel price change, and other market conditions. Each of 11 other firms occupies a 1%–5% share, and 26 firms have less than 1% share. Considering only controllable fossil fuel generators, the three biggest firms occupy approximately 51% of the total market demand.

In addition, firms that do not have any fossil fuel units own most of the wind turbines (approximately 95% of the total capacity of wind farms in the ERCOT). Among the three biggest firms, Luminant and Calpine do not own any renewable generation units. NRG is the sole or partial owner of wind farms; however, its wind capacity (379 MW) is negligible compared with its total generation units (12,311 MW).

As a firm can own several QSEs with different names, the ERCOT traces the actual decision-making entities (DME) for each generation resource to check for any potential market-distorting activities among QSEs. A large DME, such as Luminant, NRG, or Calpine, manages more than 60 resource nodes and approximately 5–10 QSEs. With each firm-level data, I investigate the aggregated patterns of the big three firms and all other 37 firms in production quantities (Table 1.2 for descriptive statistics). Market prices for each type of firm are calculated by nodal load-weighted averages. As in Table 1.2, fringe firms also seem to withhold their sales in the day-ahead market because 80% of the realized commitments in the real-time market are sold through the day-ahead market. Even if the extent of these firms’ withholding is significantly smaller than the mitigation amounts by big firms (big firms sell only 49% of the real-time market quantities in the day-ahead market), it is somewhat different from the consistent fringe firms’ strategies in the Iberian electricity market, as demonstrated by Ito and Reguant (2016). They

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19 Figure D2 in the appendix shows that the market shares of the four biggest firms, including Luminant, Calpine, NRG, and CPS (City Public Service), have consistent patterns over the last five years. In this paper, however, CPS, which owns 4%-5% of the market share, is not classified as a dominant firm because it is municipally owned.
indicated that in the Iberian market, the dominant firms always undersell, whereas fringe firms consistently oversell in the day-ahead market to exploit price differentials.

However, the different small-sized firms’ aggregated strategies in the ERCOT can be explained by a few idiosyncratic market conditions. First, as the ERCOT employs the nodal market, local marginal pricing may divide the market into several independent markets during certain times. In the localized market, even mid-sized firms with 2%–3% market share and classified as fringe firms in this paper may sometimes exert market power and engage in price discrimination. Second, and maybe more importantly, some small-sized generators are owned by large factories or other industrial facilities and sell their redundant electricity only through the spot market, which can also supplement the underselling patterns in aggregated quantities of small-sized firms.  

1.3.3. Wind Generation

The increase in installed wind capacity in the ERCOT has significantly reduced electricity market prices and pollution. However, the integration of wind generation into the electricity market may involve byproducts. First, given that large-scale energy storage is lacking in most areas, wind generation intermittency adversely affects the market as it increases supply volatility. Figure 1.4 indicates the hourly mean (dotted lines) and 95% confidence intervals (error bars) of wind generation. The figure demonstrates that the ranges of confidence intervals have significantly increased with relatively less increase in mean values during a period when installed wind capacity in the ERCOT has increased by 65% from 2011 to 2015. More specifically, the pattern of hourly wind variances based on 15-minute interval wind generation indicates quadratic growth with the increase in wind capacity.  

Second, Figure 1.5 indicates that wind forecast errors can increase as the actual wind

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20 Some generators in the ERCOT are owned by large industrial facilities, such as Air Liquide Large Industries US LP, Equistar Chemical LP, Exxon Mobil Refining and Supply Company, Dow Chemical, Texas Medical Center, and Union Carbide Corp.

21 Figure D3 in the appendix shows the monthly average wind volatility for 15-minute wind generation in an hour. It demonstrates the consistent increases in wind variance as more wind is integrated into the system.
generation (MWh) increases. Wind forecast errors are calculated by “a realized wind generation in real-time market minus a forecasted wind generation in the day-ahead market.” The figure indicates that as realized wind generation in the real-time markets increases, forecast errors also increase (more dispersed errors on the right-hand side of the figure). Additionally, it depicts an increasing trend of forecast errors (i.e., when realized wind is low, the value is more likely to be less than the forecasted values in the day-ahead market; thus, forecast errors tend to be negative). When actual wind generation is high, it is more likely that the value is greater than expected; thus, the forecast errors tend to be positive. This forecast uncertainty, caused by the limited predictability of wind drives asymmetric wind supplies over sequential markets, as wind generation sold through the day-ahead market should depend on the forecasted wind at the time.

Third, even with significantly improved volatility and forecast uncertainty, under the concentrated deregulated electricity market, the supply increases from the wind generators that have (almost) zero marginal cost would affect the intertemporal strategies of the dominant firms to maximize profits. The behavioral changes of dominant firms would greatly impact market prices and system reliabilities in the context of inelastic electricity demands.

1.3.4. Data

The empirical work in this paper has been conducted using data from three sources: (most of them from) publicly available datasets on ERCOT’s website (http://www.ercot.com), fuel cost data from the energy data service company ABB, and weather data from NOAA. I examine five-year historical data from the ERCOT electricity market, which starts from June 30, 2011, and continues through June 1, 2016. As I use hourly data, there are 43,176 observations for various dependent and independent variables.

1.3.4.1. Dependent Variables

In this paper, I find prediction functions for 15 dependent variables, which comprise hourly
nodal-load-weighted market clearing prices and hourly aggregated output decisions by the dominant and fringe firms in sequential markets. As mentioned in Section 1.3.1, the firms make a total of four output decisions across a physical market (one), an AS market (one), and a virtual market (two, buying and selling) in the day-ahead market. I aggregate each output decision by each firm type (dominant and fringe firms). Because the market clearing prices for the physical and virtual markets in the day-ahead market vary by resource nodes (Appendix B1), I calculate nodal load-weighted averages for the prices of each type of firm. Market clearing prices for the AS market are market-wide. For the real-time market, I estimate cleared quantities and clearing prices in the physical markets, which encompass all supply-side activities by conventional generators in the market. Again, the output decisions are aggregated and the prices are calculated using nodal-load-weighted averages. Table 1.1 and Table 1.2 show the descriptive statistics for the dependent variables and Table 1.3 shows a list of the dependent variables estimated using machine learning methods.

The data from the ERCOT show a detailed picture of the market, which includes information for all types of bids to buy and sell electricity submitted at each resource node, clearing prices, and cleared quantities for the bids at the nodes. Furthermore, it includes all bids, clearing prices, and cleared quantities for the virtual market and for AS. The day-ahead market data have hourly frequency, but the data for the real-time markets use 15-minute intervals. Therefore, I average the nodal clearing prices in the real-time market by their load weights and add up the metered net outputs from each resource node to change them to hourly values.

The identifiers of all market participants for the physical (a three-part supply offer) and the AS market in the day-ahead market and actual production in the real-time market are resource node names. There are 676 resource nodes in the ERCOT as of 2016, of which 493 nodes are connected to fossil fuel generators. Fossil fuel generators that have been consistently active and are owned by the same firm for the time period of this analysis are connected to 469 nodes. The owners of generators connected to the other 24 nodes have changed during the data time period, and I exclude them from my analysis. Each resource node represents approximately
one to four generators affiliated with the same power plant. Each power plant has a single owner except for those connected to 37 nodes. These resource nodes with multiple owners are simply classified as fringe firms in this paper and are aggregated to that category. I obtain the data that indicate the relation between each resource node name and the owner of generators, DME (firm names). There are 40 DME with fossil fuel units. For the virtual market, however, the identifiers are QSE names. Using another dataset that indicates resource node names managed by QSE, I find the relation between DME and QSE. Thereafter, I aggregate all market activities at the firm level.

1.3.4.2. Independent Variables

A prediction of prices and heterogeneous power plants’ generation decisions in the electricity market involves diverse factors that range from economic and engineering variables such as input price (fuel costs), time dependent market demand, and previous output decisions to exogenous weather events such as temperature, storms, and drought. I employ 256 distinct independent variables to predict the load-weighted market prices and firm-level output decisions. I specifically obtain data for wind generation sold in the day-ahead (hourly) and real-time markets (15-minute intervals), as well as data on hourly wind forecasts from the ERCOT. Production decisions of the generators, excluding coal and natural gas, are not controllable and do not respond to hourly market conditions. Thus, hourly generation from nuclear (12% of the market share) and others (biomass, hydro, solar, and imported quantities) that have less than 1% of the market share in total are included for covariates. I obtain hourly real-time backcasted demand per sink node where the energy is actually withdrawn and hourly zonal demand in the real-time market from the ERCOT database. The demand for electricity in the real-time market is almost perfectly inelastic to a price change in a short-run because only few consumers are able to adjust the consumption in response to changing market conditions. I include dummy variables to explain time fixed effects: year, quarter, month, week/weekend, holidays, day of week, hours, and on/off peak demand.
Furthermore, I obtain fuel prices, such as monthly coal prices and daily natural gas prices paid by power plants in Texas, estimated by the ABB. Finally, hourly dummies for extreme weather events such as blizzards, coastal floods, dense fog, drought, dust storms, extreme cold weather, flash floods, floods, winter storms, and so on are obtained from NOAA. All regional hourly temperatures in Texas are obtained from the same source. These fuel costs and weather datasets add 42 more variables. To find prediction functions for the dependent variables, I use the 24-hour lagged values of 256 independent variables and a dependent variable. Therefore, the total number of right-hand-side variables used for the estimations is actually 6,168.

1.4. Machine Learning Method

1.4.1. Artificial Neural Networks

I use dynamic neural networks to predict a counterfactual time series for production decisions and market prices. The neural networks may outperform other machine learning algorithms in a study of the electricity markets for the following reasons.22

First, when using neural networks, one does not need to specify a functional form to define the relation between a covariate and dependent variable. In the context of the electricity market, where various time-varying covariates—fuel costs, nodal demands, and weather events—affect the production decisions of generators as well as electricity prices, it is almost impossible for one to correctly specify all the relations with a hand-curating functional form such as a logarithm, a form of splines, or so on. Instead, using neural nets with the proliferation of datasets in the electricity market, we may simply let the data tell us which forms work best. In addition, given that neural nets employ numerous neurons, each of which largely comprises nonlinear transformations of a linear equation of a set of covariates, they can endogenously capture the

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22 There are a variety of machine learning algorithms other than the neural networks: LASSO, decision trees, a combination of models (bagging), support vector machines, and deep learning. Appendix C provides more details on dynamic neural networks. In particular, the section addresses how dynamic neural networks are generally formulated, how we can find optimal prediction functions and measure their prediction accuracies, and what complementary tools are used in that the method to prevent potential overfitting.
effects driven by some combinations of covariates within the method’s nature of mixed predictors (Appendix C). Additionally, by setting a regularization parameter, one can also perform the selection on observable tasks, which is essentially what LASSO does, while retaining the mixture nature and data-driven model selection.23

Second, with the dynamic constraints of fossil fuel fleets, a generator’s production decisions are recursively determined. Market prices are also a time-dependent recursive process. Because dynamic networks have memory by inference from the lagged values of dependent and explanatory variables, they can be trained to learn sequential or time-varying patterns. After being trained, the dynamic network makes predictions based on its own predicted values (called “closed-loop predictions” in machine learning literature) and automatically iterates the prediction process. In other words, after training the model, we can generate the time paths with an initial value of dependent variables and a set of covariates corresponding to the time span that we want to generate. In this paper, I train the prediction functions and make closed-loop predictions for 2012–2015 market outcomes.

1.4.2. Estimation Model

Using a detailed picture of the strategy of all market participants, I classify them as dominant firms (Luminant, Calpine, and NRG), who individually occupy more than 10% of the market share, and fringe firms (all other firms), where each owns 1%–2% of the market share. For the two firm categories, I aggregate the cleared quantities and calculate weighted average nodal prices with respect to the quantities sold at each node as mentioned in Section 1.3.4. Next, I develop prediction functions for the cleared quantities and clearing prices in a physical market, an AS market, and a virtual market. For the real-time market, I estimate cleared quantities and clearing prices in the physical markets.

23 LASSO is able to do the same task, but to predict targets, it still needs to specify functional forms of covariates and the relationships among covariates.
For the day-ahead market estimation models, I use the following equation (in conventional regression notation) to train a learning algorithm because the day-ahead market is cleared at 1:30 p.m. for the next day’s operating hours (00:00–23:00 hours):

\[
\begin{bmatrix}
P_{h_1,t}, P_{h_1+1,t}, P_{h_1+2,t}, \ldots, P_{h_1+23,t}
\end{bmatrix}
= F\left(P_{h_1,t-1}, P_{h_1+1,t-1}, \ldots, P_{h_1+23,t-1}, X_{h_2,t}, X_{h_2-1,t}, \ldots, X_{h_2-23,t-1}\right),
\]

where \(P_{h_1,t}\) denotes the price for hour \(h_1\) (00:00) and day \(t\), \(X_{h_2,t}\) denotes a covariate matrix containing all datasets mentioned in the data section for hour \(h_2\) (13:00) and day \(t\). In other words, the 24-hour day-ahead market prices on a day are estimated on the basis of 24-hour prices on the previous day and 24-hour lagged values for a covariate matrix with respect to 13:00 hours.

Function \(F\) denotes a prediction model estimated by the dynamic neural networks:

\[
\begin{bmatrix}
Q_{h_1,t}, Q_{h_1+1,t}, Q_{h_1+2,t}, \ldots, Q_{h_1+23,t}
\end{bmatrix}
= G\left(Q_{h_1,t-1}, Q_{h_1+1,t-1}, \ldots, Q_{h_1+23,t-1}, X_{h_2,t}, X_{h_2-1,t}, \ldots, X_{h_2-23,t-1}\right)
\]

Quantities cleared through the day-ahead markets \(Q_{h_1,t}\) are estimated using the same format and function. \(G\) denotes a prediction function. The process of finding these prediction functions \(F\) and \(G\) has been performed for an AS market and a virtual market as well. Each dominant and fringe firm has different prediction functions.

As the real-time market is cleared every 5 minutes and data acquisition is at 15-minute intervals, I change the data format to hourly values. I use a following equation for estimation:

\[P_h = I(P_{h-1}, P_{h-2}, \ldots, P_{h-6}, X_h, X_{h-1}, \ldots, X_{h-23}, \Phi_h, \Phi_{h-1}, \ldots, \Phi_{h-23})\]

where \(P_h\) denotes price at hour \(h\), and \(X_h\) is a covariate matrix at hour \(h\). In addition, the prediction functions include \(\Phi_h\), which denotes clearing prices and cleared quantities in the day-ahead market because all market outcomes in the real-time market occur due to the results of the first market. Function \(I\) denotes a prediction model for the real-time market. The quantities awarded are also estimated by the same format, and each firm type has different prediction functions.
The counterfactual time paths for market outcomes in the day-ahead market have been made from functions $F$ and $G$ first, and the results for the real-time market have been made by function $I$ using the predicted results from the day-ahead market. These two steps replicate an actual sequential market process.

### 1.4.3. Identification Strategy – Causal Inference with Counterfactuals

I present an alternative method for deriving a causality with counterfactual predictions using machine learning methods. Angrist and Pischke (2009) note the fact that the observed difference in outcomes involves selection bias. If one can run a truly randomized treatment–control experiment, then selection bias is eliminated and those treated represent an unbiased random sample of the population. The control group provides an estimate of the counterfactual: what would have happened without treatment. However, this ideal way of estimating treatment effects is quite expensive and even impossible in most circumstances; thus, it is worth finding a feasible alternative to predict the counterfactual. Varian (2014) proposed the Bayesian structural time series method to build a model that predicts the time series of visits to a website to estimate the impact of an advertising campaign on visit numbers. Comparing the actual visits with the counterfactual visits provides an estimate of the causal effect of advertising. Using a similar approach, Burlig et al. (2017) deployed machine learning methods (LASSO) to predict counterfactual electricity consumption at treated schools (what if the treated schools were not treated) to measure the impacts of energy efficiency investment at public K-12 schools in California. Hartford et al. (2016) proposed a novel way to incorporate an instrument variable (IV) into neural nets and derive a causal inference with the counterfactual predictions.

In this paper, I use dynamic neural nets to find the prediction models and construct counterfactual time paths for hourly prices and quantities in the forward and spot markets. These counterfactual paths describe what would have happened to electricity prices and supplies if there had been either lower or higher exogenous wind generation. Accordingly, I consider the difference between counterfactual paths in order to estimate the heterogeneous treatment effects.
of increase in wind generation on the market prices and quantities across different firms at
certain hours and in certain seasons. To state this in a slightly more formal way, I use the
following equation:

\[ \beta = \frac{1}{T} \sum_{t=1}^{T} (y_t - \hat{y}_t). \]

For simplicity, I use a representative variable \( y_t \) (actual values); however, various
dependent variables are used in this paper: the cleared quantities and clearing prices in physical
markets, AS offers, and virtual bids to buy and offer for dominant and fringe firms in the day-
ahead market, and the cleared quantities and clearing prices in the real-time markets (see Table
1.3 for the entire list). \( \hat{y}_t \) can be counterfactual time paths that describe what would have
happened to \( y_t \) if there had been, for example, (1) a 20% increase in wind generation involving
increased wind volatility and forecast errors, as in Figure 1.7 and Figure 1.8; (2) a 20% increase
in wind volatility with the business-as-usual (BAU) setting for all others; 3) a 20% increase in
wind forecast errors with the same BAU setting for others; and (4) a 20% wind generation
increase with fixed wind volatility and forecast errors. Thereafter, \( T \) is adjusted for a desired time
span. Each of the causal inferences using the machine learning method with regard to the
question above is addressed in Section 1.5.

1.4.3.1. Counterfactual Wind Generation Increase

To predict counterfactual market outcomes, I first generate a counterfactual wind generation
increase. To do this, I simply multiply actual wind generation data for 2012–2015. For example,
for a 20% increase, I multiply the actual data by 1.2 for a counterfactual wind path. Despite its
simplicity, this approach could replicate the actual increments of wind generation shown in the
data. This is because in the ERCOT, wind turbines have been built in almost the same region;
thus, the pattern of aggregate generation in recent years is almost the same as the multiplied
aggregated wind generation pattern, with the far lower installed capacity of years ago. Figure 1.4
indicates the actual increase from 2011 to 2015, and Figure 1.7 depicts the hourly average of the

27
counterfactual 20% wind increase for 2012–2015, which could replicate a decent counterfactual pattern. This circumstance enables me to directly calculate the volatility increase by simply multiplying a squared constant number because I define the term as hourly variances of 15-minute wind generation. Generating the forecast error changes, however, requires more attention. I also multiply the actual forecast errors, estimate the slope of the line shown in Figure 1.5, and add a slight increasing trend. All the counterfactual paths for volatility and forecast uncertainty are shown in Figure 1.8. As I test the generated paths by checking for hourly mean and variance and the fit of the collocation function to the trend, the generated paths can all reflect the actual path well.

1.4.4. Performance–Prediction Accuracy

This section describes the prediction accuracy of the dynamic neural networks with MSE and other graphical demonstrations. To do that, I set aside 2015 data for test samples and randomly split the remaining dataset into training and validation samples.24 Furthermore, I find prediction functions for all market outcomes and measure the prediction errors (MSE). For the performance comparison with a conventional panel regression, I set aside 2015 data as done in the machine learning method, use the same set of covariates, and run a simple linear regression. The estimation model for the day-ahead market can be obtained by seemingly unrelated regression (SUR) because each of the 24 dependent variables on the day-ahead market is estimated by the same dataset, whereas the model for the real-time market is the same as the formulation for the machine learning method in the previous section.

Table 1.3 indicates the comparative results by the square root of MSE for all prediction models. RMSE (Open) denotes the square root of MSE for open-loop prediction results, which

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24 For the actual predictions used for causal inference in this paper, I use all the data set with random sample splitting for a training (70% of data randomly selected) and validation samples (the other 30 %) and iterate the process. Then, I find 50 prediction models for each dependent variable and take the average of predictions from the 50 models, mainly because trainings with random sample splitting can be sufficient to generalize the prediction models and prevent potential overfitting. Furthermore, predictions of good quality can generally be obtained by combining a small number of carefully chosen models. Section C in the Appendix explains this in greater detail.
are just one-time-step forward predictions based on the known dependent variable. RMSE (Closed) is the square root of MSE for multi-time-step prediction results for 2015 and is generally greater than RMSE (Open) as the error is basically accumulated as the time path extends. The right-hand column, RMSE (Panel), shows the prediction performances of a simple linear panel regression for a comparison. From the table, we can see that dynamic neural networks significantly outperform simple panel regression in their predictive power over all 15 prediction functions.

Figure 1.6-1 indicates how well the results predicted through the dynamic neural networks match with the actual targets. The $x$-axis shows the values for targets, and the $y$-axis shows the values for predicted outputs. If scattered points take the shape of a line with a slope of 1 (predicted and actual outputs become closer), then it would demonstrate that the prediction models perform better. Overall, the prediction functions provide reasonably strong predictions and can replicate the actual targets. Specifically, they predict prices and cleared quantities in the day-ahead market, awarded quantities in the virtual market, and actual generation commitments in the real-time market very well, whereas there are relatively fewer prediction accuracies for clearing prices in the real-time market. Generally, if there are more large outliers in the targets as in the spot prices, then it is difficult to predict not only the outliers but also the overall targets because the estimators that minimize MSE are largely influenced by the outliers.\textsuperscript{25}

Finally, Figure 1.6-2 depicts some samples of prediction performance for market prices in a sequential market in July. The predictions can replicate the actual trend of the time series and find the timings of price spikes even if they could not perfectly predict the extent of shocks. Figures D7 and D8 in the Appendix show the additional prediction performances. Armed with these decent prediction functions, I estimate causality in the next section.

\textsuperscript{25} To achieve better performance in a future study, one can use two-step predictions: the first layer determines whether a target is outliers or not and second one actually estimates the target if the target is not an outlier. This approach is analogous to the estimation using mixture probability distribution that comprises binomial and normal distributions.
1.5. Results

I present how a wind generation increase would affect market outcomes, with the focal view of market prices and firms’ strategic responses. To do so, I investigate the price differential defined as forward minus spot prices and firms’ intertemporal decisions in a sequential market by investigating what fractions (%) of their total productions are sold through a forward market. This relative analysis is important because the supply increase from wind generators with (almost) zero marginal cost should decrease both forward and spot prices and should automatically occupy the market shares of other conventional generators. If we simply compare the prices and quantities before and after wind changes, then the comparison will show these simple decreasing trends. Using these two metrics for relative changes, if we expect the rational behavior of market participants, then they will increase the fraction to maximize their profits when the FPP increases, and they will decrease the ratio when the FPP decreases.

In the first two subsections, I mainly investigate the FPP and ratios. I analyze the overall implications and characterize the impacts by decomposing wind generation into wind forecast uncertainty and volatility and wind generation itself. Based on the analysis, I identify the rationale behind the changes in Section 1.5.3.

1.5.1. Forward Premium

Table 1.4 summarizes the impact of a 20% increase in wind generation based on the generation data from 2012 to 2015, which is an approximate 800 MWh increase on average. I predict the four-year counterfactual time paths for prices in the day-ahead and real-time markets and calculate the FPP for the baseline and counterfactual scenarios.

Before discussing the results in detail, it is worth noting that the data for electricity market prices are not normally distributed due to its skewness, fat tails, and extreme values. I use standardized statistical test methods (the Jarque–Bera test and Lilliefors test) to test the normality of all market prices in the ERCOT and perform graphical normal fits. I find that the price data
strongly reject the null hypothesis of normality and so do the counterfactual time paths. Thus, I employ nonparametric tests to measure the $p$-values of point estimates and use the bootstrap method to calculate the standard errors for estimated average treatment effects. Specifically, I employ the Mann–Whitney U test (MWU in Table 1.4) to test the null hypothesis that the counterfactual FPP statistically differs from the baseline results. In addition, I run the Wilcoxon signed-rank test (SR in Table 1.4) for one-sided hypothesis testing, with a null that the counterfactual FPP is statistically greater than the baseline FPP. Furthermore, I use a bootstrap with 100,000 samplings to estimate the standard error of the point estimate, as shown in parentheses in Table 1.4, and calculate the confidence intervals shown in Figure 1.9, Figure 1.11, and Figure 1.13.

As predicted by the theoretical model in Section 1.2, the FPP increases with wind generation. Table 1.4 indicates that the increase in wind generation has increased the market-wide FPP by $0.30, which is equivalent to a 16% increase in the FPP. In addition, during the low net load period, when electricity demand is low and the wind generation is relatively high, the wind impact is larger and thus induces the greater FPP change. With the changes, consumers (retailers) are likely to be worse off, as they have to pay higher prices to ensure their purchases in advance through the forward market. Production inefficiencies also arise when the generators choose different quantities in the forward (scheduled) and spot markets (realized commitments) to either manipulate the prices or arbitrage the systematic price differentials.

Specifically, if we consider the firm-level FPP, dominant firms have a $0.36 increase on average, which is equivalent to an 18% increase. Fringe firms have consistently smaller impacts over different seasons, and the extent is $0.25 or an approximate 13% increase on average in total. Because these results are based on hourly average prices weighted by nodal loads for each type of firm, heterogeneity results from the combination of firms’ different responses and nodal congestion. When the transmission lines reach the maximum capacity, demand cannot necessarily be satisfied by the lowest cost generator and the nodal prices vary significantly. The differences are more obvious through hourly changes in the FPP shown in Figure 1.9. Dotted
lines indicate the mean values, and shaded areas indicate the 95% confidence interval obtained by the bootstrap method. The greatest price differential between dominant and fringe firms occurs between 6 a.m. and 8 p.m., when the systems are more likely to be congested with relatively higher demand.

Notably, the FPP soars at both 8 a.m. and 6 p.m., when net load (market demand minus supplies from renewables and nuclear) starts increasing and decreasing, respectively. During the transition stages, the residual demand for dominant firms in the real-time market should be more inelastic because some of the generators owned by fringe firms go offline and require additional startup costs. Hortaçsu and Puller (2008) indicated that the supply curve of fringe firms becomes more inelastic when they face more adjustment and participation costs in the real-time market. The theoretical model in Section 1.2.2 also indicates that with the increase in wind generation, the FPP increases when the residual demand in the real-time market becomes more inelastic.

1.5.1.1. Decompositions of the Impacts

Table 1.6 presents what specific factors actually have an influence over the FPP. Forecast errors and wind generation itself (without changes in volatility and forecast errors) increase the FPP, whereas volatility has a relatively small negative impact on prices but is not statistically significant.

This is informative because an increase in market volatility is likely to produce more price spikes in the real-time market, but its impact is insufficient to make statistically significant changes because the price spikes are relatively rare events. In addition, the increased 15-minute wind volatility within an hour is difficult to predict from the day-ahead market; thus, its impact on the day-ahead market outcomes should be negligible (e.g., wind forecast information given to market participants in the forward market is hourly based). Figure 1.11 also supports this argument. A volatility increase would create a negative FPP due to the occasional real-time market price spikes when the market demand is normally high (and volatility is high).
Forecast errors, however, would produce a statistically significant positive FPP. When consumers (retailers) expect that the forecasts have insufficient predictability and that the price in the real-time market would become more uncertain with the increase in wind generation, they are likely to ensure their purchases in advance through the forward market. In other words, this increase in forecast errors would elicit responses from the consumer side rather than those from the supply side. Figure 1.11 also demonstrates this argument. The hourly pattern of FPP changes driven by increased forecast errors resembles the shape of hourly electricity demand.

The most remarkable observation from Table 1.6 is that an increase in wind production itself is the main factor in FPP changes, and this factor induces some heterogeneous responses from firms of different sizes. There is a 75% greater increase in the FPP for dominant firms than for fringe firms. This is reasonable because both volatility and forecast errors are almost completely exogenous without regard to firm sizes.26 However, as the firms know the average patterns of wind generation, they can have some different strategic responses based on their expectations. However, we need to incorporate firms’ different strategies to investigate this in more detail.

1.5.2. Firms’ Responses

I define quantities sold in the day-ahead market as an aggregate of the cleared quantities in the physical, virtual, and AS markets. I also define quantities for the real-time market as firms’ final committed generation in the market. In the ERCOT, dominant firms only sold 48.3% of the total production through the day-ahead market, whereas fringe firms sold 80.9% of production on average from 2012 to 2015. During this time, there also has been a consistent FPP.

Table 1.5 indicates a consistent pattern of firms’ responses to the increase in wind generation. Dominant firms do not change their fractions even with significant increases in wind

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26 Hortacsu et al. (2017) demonstrated that strategic sophistication increases with the size of the firm. There is a chance that a dominant firm can better respond to the highly unpredictable exogenous events. Even if the FPP seems almost the same, the extent of responses from dominant and fringe firms are somewhat different in this paper as well. Sections 5.2 and 5.3 present the details.
generation (a 30% increase or 1200 MWh). All the small changes shown in the table are not statistically significant. Note that even if the ratio of a firm did not change at all with the wind generation increase, this does not mean that the firm did not change its behavior. For example, an increase in wind generation should decrease a conventional generator’s final sales in the real-time market. If the firm did not respond, then the ratio should increase. Thus, a more reasonable inference is that the same fraction after the wind increase demonstrates that the firm reshuffled the sequential quantities to set its old optimal ratios. Thus, the dominant firms’ responses are counter-intuitive if we account for the increased FPP in the market.

There still remains a chance that wind generation equally influences the day-ahead and real-time markets and that their selling quantities have simply been determined by the market conditions. However, Table 1.2 and Figure 1.3 show that only 5% of wind has been sold in the day-ahead market on average and that the absolute quantities sold in the day-ahead market are almost the same over 2011–2015. The counterfactual predictions reflect the behavioral responses based on the conditions. In addition, the individual prediction results used to calculate the ratios actually indicate that the firms decreased final committed generation in the real-time market by 280 MWh on average and decreased sales in the day-ahead market by 168 MWh, with a 20% increase in wind generation, or 800 MWh on average. In other words, the firms decrease their sales in the day-ahead market more than they decrease the additional quantities sold in the real-time market in order to set their old optimal quantities.

Figure 1.10 presents the details of the firms’ hourly responses. The thicker lines denote the results for higher wind generation. Dominant firms maintain almost the same allocation of sales until 8 a.m.; they somewhat reduce the quantities they sell from 9 a.m.–7 p.m.; and they increase the fraction after 7 p.m.

The result for fringe firms in Table 1.5, however, shows a consistent increase in their allocations of day-ahead market sales as wind increases. These firms start from 81% at the baseline and consistently increase their fractions. All the changes are statistically significant, with almost zero $p$-values. Figure 1.10 shows more obvious patterns of their strategic changes.
Specifically, the shape of increased fractions is similar to the pattern of diurnal hourly wind generation, as shown in Figure 1.4. In other words, when wind is high, they are more likely to set more fractions of their sales in the day-ahead market to exploit the positive price differentials created by wind generation.

These heterogeneous firm responses are analogous to those found in the Iberian market. Ito and Reguant (2016) demonstrated that dominant firms with market power withhold production in the first market to set a higher marginal price, whereas fringe producers that do not have substantial levels of market power exploit the price differential. My results empirically show how price-discriminating firms would change their strategic behavior in sequential markets, with residual demand shifts. Dominant firms continue to engage in intertemporal price discrimination, but fringe firms exploit the price differential.

1.5.2.1. Decomposition of the Impacts

Again, greater integration of wind generation involves byproducts, each of which has a different impact on the market outcomes. Table 1.7 presents the details. Similar to the results for the FPP, wind generation with fixed volatility and forecast uncertainty induces the heterogeneous responses of firms. As the wind generation increases, dominant firms consistently decrease their fraction of total sales in the day-ahead market and fringe firms continue increasing their fractions. We can find that wind generation itself mainly drives the heterogeneous responses observed in the aggregated pattern.

With forecast errors, however, both firm types sell more fractions through the day-ahead market. Through the more detailed investigation in the following section, I find that this increase is mainly driven by demand shifts in the day-ahead market.
1.5.3. Implication of Wind Generation in Different Channels

The empirical models clearly demonstrate that forecast errors and wind generation with other fixed components would increase an FPP, while volatility slightly decreases the FPP. The results also show that the three components all have different channels through which to affect the firm strategy. This section presents additional empirical evidence consistent with the hypotheses in the previous sections to support the following arguments: (1) with the integration of only wind generation, dominant firms would withhold quantities, which increases FPP; (2) with the increase in forecast errors, market demand shifts to the forward market; and (3) an increase in volatility creates more price spikes in the real-time market.

1.5.3.1. Dominant Firms’ Intertemporal Price Discrimination

A wind generation increase with fixed other components clearly induces heterogeneous strategic responses of firms, with the most significant impacts on an FPP. With the increase in the FPP, selling more in a forward market should be more profitable for generators. From the empirical results, however, the dominant firms appear to move in exactly the opposite direction of the pricing gap: they show relatively fewer sales in the day-ahead market, with an increase in the FPP. The rationalization of this consistently money-losing behavior by large firms in this paper is based on their intertemporal price discrimination. Specifically, dominant firms continue engaging in price discrimination, thus creating higher pricing gaps in the sequential market, whereas firms that do not have substantial levels of market power exploit the price differential created by the big firms. The bottom panel of Figure 1.12 shows the firms’ different strategies.

In addition, the FPP differentials for the two firm types arise from a combination of firms’ different responses and nodal congestion. Figure 1.13 indicates that FPP differences for dominant and fringe firms exist when dominant firms withhold more sales and decrease the fraction below their 48% ratio from 5 a.m. to 9 p.m. The greater increase in the differences, especially from 4 p.m. to 6 p.m., reflects a higher probability for system congestion during these hours due to the more segmented nodal market.
1.5.3.2. Demand Shifts to the Day-Ahead Market with Uncertainty

With increased forecast error, the other market conditions, including wind generation, remain the same. To illustrate the evidence of demand shifts, we can simply investigate the individual values of clearing prices and cleared quantities because there is no other exogenous supply increase that affects both day-ahead and real-time market outcomes. With the forecast error increase driven by a 20% increase in wind, 112 MW more, on average, are cleared through the day-ahead market, and no significant changes in quantities are cleared in the real-time market as expected. The prediction results also show consistent increases in day-ahead prices but decreases in real-time prices. This increased price in the day-ahead market can reject another possible hypothesis that firms may simply supply more through the day-ahead market with increased forecast errors. Even if the supplies might have moved to the day-ahead market, we can conclude that the impact of demand shifts should be larger because of the price increase. Additionally, the estimation results from Figure 1.11 and Figure 1.12 show almost the same FPP and same directional changes in the responses of dominant and fringe firms. This means that the forecast error increase is exogenous without regard to a firm type. Finally, the hourly pattern of FPP changes also resembles the shape of hourly electricity demand. All these points considered show evidence of demand shifts to the day-ahead market from the real-time market when there is an increase in forecast errors.

1.5.3.3. More Frequent Price Spikes with Market Volatility

As shown in the top panel of Figure 1.11, the increase in market volatility is likely to create more price spikes in the real-time market. More specifically, from the predicted price paths, the volatility increase accompanied by 20% more wind generation increases the real-time prices by $0.06 on average; however, the impacts are concentrated during peak hours, as shown in the figure. In addition, the volatility does not produce any statistically significant changes in the day-ahead prices. Thus, the changes in Figure 1.11 reflect the average effects resulting solely from the increases in real-time market prices. In addition, the estimation results indicate that the price
variances in the real-time market are increased mainly during the periods of 7–10 a.m. and 4–8 p.m., which also supports the hypothesis that the real-time market prices solely incorporate the volatility increases.

1.6. Conclusion and Discussion

I have examined the impact of increased wind generation on market efficiency through the channels of the FPP and firms’ heterogeneous responses in sequential markets. I implement theoretical models to outline the basic framework and employ a novel machine learning method to estimate the causal effects based on counterfactual predictions. Consistent with the theoretical prediction, the empirical results reveal the challenges of achieving market efficiency with increased wind generation when the market is subject to the exercise of market power. Even in the absence of the main adverse factors, such as volatility and forecast uncertainty, wind generation creates the systematic FPP and causes market inefficiency because firms exert market power in the forward market and engage in intertemporal price discrimination in conjunction with the changes. In addition, I demonstrate that the two main adverse factors have idiosyncratic channels to affect the sequential markets: (1) increased market uncertainty caused by forecast errors shifts demand from the spot to the forward market, and (2) volatility generates more frequent price spikes in the spot market. The variety of ways in which wind generation affects market outcomes highlight the importance of taking a wide variety of factors into consideration when assessing the costs of renewable generating technologies. Beyond the policy applications, this paper represents a possible extension of machine learning method to the analysis of industrial dynamics.
Table 1.1: Summary Statistics of Main Variables – Prices. This table presents descriptive statistics for market prices. A few issues need to be addressed. First, the market prices in ERCOT are generally quite volatile, as they range from negative $4,105 to $5,102. Second, the market prices in the real-time market are more volatile than the day-ahead prices. Finally, the mean and median of the forward price premium (FPP) show that there is a positive forward price premium. ‘REGDN’ and ‘REGDN’ mean Regulation Up and Regulation Down, respectively. ‘RRS’ is responsive reserve and ‘NSPIN’ is non-spin reserve. In general, the purpose of responsive and non-spinning reserves is to protect the system against unforeseen contingencies (e.g., unplanned generator outages, load forecast error, wind forecast error) rather than for meeting normal load fluctuations. Regulation reserves are a type of capacity that responds every four seconds, either increasing or decreasing as necessary to fill the gap between energy deployments and actual system load.

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA price</td>
<td>8,764,728</td>
<td>32.6</td>
<td>63.9</td>
<td>-283.8</td>
<td>20.6</td>
<td>26.0</td>
<td>34.2</td>
<td>8214.0</td>
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<tr>
<td>RT price</td>
<td>8,764,728</td>
<td>30.5</td>
<td>76.8</td>
<td>-4105.0</td>
<td>19.4</td>
<td>23.9</td>
<td>29.8</td>
<td>5102.4</td>
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<tr>
<td>FPP (2012)</td>
<td>1,783,152</td>
<td>2.6</td>
<td>48.0</td>
<td>-2989.1</td>
<td>-0.9</td>
<td>1.7</td>
<td>4.9</td>
<td>1502.1</td>
</tr>
<tr>
<td>FPP (2013)</td>
<td>1,778,280</td>
<td>1.5</td>
<td>45.5</td>
<td>-3713.7</td>
<td>-0.6</td>
<td>2.7</td>
<td>7.0</td>
<td>4141.7</td>
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<tr>
<td>FPP (2014)</td>
<td>1,778,280</td>
<td>1.8</td>
<td>71.3</td>
<td>-4812.0</td>
<td>-0.8</td>
<td>2.6</td>
<td>7.6</td>
<td>8170.8</td>
</tr>
<tr>
<td>FPP (2015)</td>
<td>1,778,280</td>
<td>1.6</td>
<td>46.6</td>
<td>-3093.0</td>
<td>-1.1</td>
<td>1.1</td>
<td>4.1</td>
<td>2164.4</td>
</tr>
<tr>
<td>FPP (ALL)</td>
<td>8,764,728</td>
<td>2.1</td>
<td>76.7</td>
<td>-4812.0</td>
<td>-0.9</td>
<td>1.8</td>
<td>5.7</td>
<td>8170.8</td>
</tr>
<tr>
<td>AS price (REGDN)</td>
<td>43,176</td>
<td>6.3</td>
<td>9.1</td>
<td>0.0</td>
<td>3</td>
<td>4.3</td>
<td>7.3</td>
<td>310.1</td>
</tr>
<tr>
<td>AS price (REGUP)</td>
<td>43,176</td>
<td>11.8</td>
<td>67.4</td>
<td>0.0</td>
<td>3.1</td>
<td>5.7</td>
<td>10.0</td>
<td>4999</td>
</tr>
<tr>
<td>AS price (RRS)</td>
<td>43,176</td>
<td>13.1</td>
<td>63.7</td>
<td>0.45</td>
<td>4.0</td>
<td>6.9</td>
<td>11.9</td>
<td>3000</td>
</tr>
<tr>
<td>AS price (NSPIN)</td>
<td>43,176</td>
<td>5.5</td>
<td>35.4</td>
<td>0.0</td>
<td>1.0</td>
<td>1.6</td>
<td>3.4</td>
<td>3000</td>
</tr>
</tbody>
</table>
Table 1.2: Summary Statistics of Main Variables – Quantities. This table presents summary statistics for aggregate quantities in MWh sold by dominant (Luminant, Calpine, and NRG) and fringe firms (all other 37 firms having fossil fuel fleets). Note that all supplies in the day-ahead market by dominant firms (Day-Ahead supply, Ancillary Service supply, and virtual supply) are less than those by fringe firms, while the final commitments (RT Final Supply) by dominant firms in the real-time market are greater than those by fringe firms. In other words, the extent to which dominant firms undersell in the day-ahead market relative to their final position is greater than for fringe firms. Also, the wind generation quantity sold through the day-ahead market is only about 5% of the final supply in the real-time market.

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dominant Firms</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(based on 3 firms)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DA Supply</td>
<td>43,176</td>
<td>4,671</td>
<td>1,989</td>
</tr>
<tr>
<td>AS Supply</td>
<td>43,176</td>
<td>1,321</td>
<td>296</td>
</tr>
<tr>
<td>Virtual Supply</td>
<td>43,176</td>
<td>736</td>
<td>547</td>
</tr>
<tr>
<td>Virtual Demand</td>
<td>43,176</td>
<td>5225</td>
<td>2371</td>
</tr>
<tr>
<td>RT Final Supply</td>
<td>43,176</td>
<td>13750</td>
<td>4021</td>
</tr>
<tr>
<td>Market Share (%)</td>
<td>43,176</td>
<td>35</td>
<td>4</td>
</tr>
<tr>
<td>Fringe Firms</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(based on 37 firms)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DA Supply</td>
<td>43,176</td>
<td>6,620</td>
<td>2,839</td>
</tr>
<tr>
<td>AS Supply</td>
<td>43,176</td>
<td>2,262</td>
<td>313</td>
</tr>
<tr>
<td>Virtual Supply</td>
<td>43,176</td>
<td>1,200</td>
<td>622</td>
</tr>
<tr>
<td>Virtual Demand</td>
<td>43,176</td>
<td>7056</td>
<td>2414</td>
</tr>
<tr>
<td>RT Final Supply</td>
<td>43,176</td>
<td>13025</td>
<td>4795</td>
</tr>
<tr>
<td>Market Share (%)</td>
<td>43,176</td>
<td>33</td>
<td>6</td>
</tr>
<tr>
<td>Wind</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DA Sold</td>
<td>43,176</td>
<td>249</td>
<td>180</td>
</tr>
<tr>
<td>RT Final Supply</td>
<td>43,176</td>
<td>4060</td>
<td>2653</td>
</tr>
<tr>
<td>Market Share (%)</td>
<td>43,176</td>
<td>11.5</td>
<td>8.3</td>
</tr>
</tbody>
</table>
Table 1.3: Prediction Errors for Test Sample (2015 Market Outcomes). This table presents a square root of mean square errors for predictions based on open-loop predictions (RMSE (Open)), closed-loop predictions (RMSE(Closed)) with neural nets, and a linear panel regression (RMSE (panel)). All prediction functions have been trained without a test sample (year 2015 data) and errors are calculated by the difference between predicted values and actual targets for the held-out test sample. One can see that neural nets significantly outperform a panel regression in predictive power.

<table>
<thead>
<tr>
<th>Variable</th>
<th>RMSE (Open)</th>
<th>RMSE (Closed)</th>
<th>RMSE (Panel)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dominant Firms</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(based on 3 firms)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DAM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DA Price</td>
<td>5.7</td>
<td>5.8</td>
<td>41.1</td>
</tr>
<tr>
<td>DA Supply</td>
<td>505.7</td>
<td>526.1</td>
<td>1563.9</td>
</tr>
<tr>
<td>Virtual Bids</td>
<td>555.9</td>
<td>590.7</td>
<td>1432.2</td>
</tr>
<tr>
<td>Virtual Offers</td>
<td>81.8</td>
<td>83.8</td>
<td>579.9</td>
</tr>
<tr>
<td>AS Supply</td>
<td>84.7</td>
<td>94.5</td>
<td>544.6</td>
</tr>
<tr>
<td>RTM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RT Price</td>
<td>11.2</td>
<td>11.5</td>
<td>66.4</td>
</tr>
<tr>
<td>RT Supply</td>
<td>220.5</td>
<td>388.5</td>
<td>2260.5</td>
</tr>
<tr>
<td><strong>Fringe Firms</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(based on 37 firms)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DAM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DA Price</td>
<td>5.9</td>
<td>5.9</td>
<td>40.1</td>
</tr>
<tr>
<td>DA Supply</td>
<td>516.0</td>
<td>554.3</td>
<td>1284.9</td>
</tr>
<tr>
<td>Virtual Bids</td>
<td>464.1</td>
<td>486.1</td>
<td>1588.8</td>
</tr>
<tr>
<td>Virtual Offers</td>
<td>78.0</td>
<td>80.4</td>
<td>1504.2</td>
</tr>
<tr>
<td>AS Supply</td>
<td>133.0</td>
<td>143.9</td>
<td>578.4</td>
</tr>
<tr>
<td>RTM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RT Price</td>
<td>10.1</td>
<td>10.3</td>
<td>66.0</td>
</tr>
<tr>
<td>RT Supply</td>
<td>202.7</td>
<td>371.4</td>
<td>1593.6</td>
</tr>
<tr>
<td><strong>Market-Wide</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DAM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AS Prices</td>
<td>5.8</td>
<td>5.8</td>
<td>31.8</td>
</tr>
</tbody>
</table>
Table 1.4: Forward Price Premium Changes (2012-2015) with 20% Wind Increase. This table presents the impacts of 20% increased wind generation (~800MW) on a forward price premium. The Mann Whitney U test (MWU above) is used to test the null hypothesis that the counterfactual forward premium is statistically different from the baseline results. The Wilcoxon signed-rank test (SR in table 5) performs one-sided hypothesis testing with a null that the counterfactual forward premium is statistically greater than the baseline premium. Standard errors for the point estimate in parenthesis were obtained by a bootstrap method with 100,000 samplings. A $0.36 increase for dominant firms is equivalent to an 18% increase on average, while a $0.25 increase for fringe firms corresponds to a 13% increase on average.

<table>
<thead>
<tr>
<th></th>
<th>Low Net Load</th>
<th>High Net Load</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dominant</td>
<td>0.52*+ (0.010)</td>
<td>0.21*+ (0.007)</td>
<td>0.36*+ (0.006)</td>
</tr>
<tr>
<td>Fringe</td>
<td>0.38*+ (0.010)</td>
<td>0.12*+ (0.007)</td>
<td>0.25*+ (0.006)</td>
</tr>
<tr>
<td>Observations</td>
<td>14688</td>
<td>11712</td>
<td>35016</td>
</tr>
</tbody>
</table>

* : p (MWU) < 0.01,  + : p (SR) < 0.01
Table 1.5: Firms’ Strategic Behavior Changes with Increase in Wind Generation. This table shows heterogeneous responses by different size of firms to wind generation increases of 10% (~ 400 MWh) – 30% (~ 1200 MWh). The percent values denote the fraction of quantities sold in the day-ahead market (through physical and virtual markets) based on the firms’ final commitments in the real-time market. The BAU column denotes their decisions for 2012-2015. The 10% to 30% increase columns show the changes in the fractions with increase in wind generation. The dominant firms significantly withhold quantities from the forward market (48% sold) in the ERCOT and would not change their strategies even with the significant amount of increase in wind generation (30% increase). Furthermore, the table shows that all the small changes are not statistically significant. The fringe firms, however, increase their selling in the day-ahead market to exploit price differentials created by wind generation.

<table>
<thead>
<tr>
<th></th>
<th>BAU</th>
<th>10% Increase</th>
<th>20% Increase</th>
<th>30% Increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dominant</td>
<td>48.3%</td>
<td>0.02</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Fringe</td>
<td>80.9%</td>
<td>0.41*</td>
<td>0.81*</td>
<td>1.21*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.004)</td>
<td>(0.008)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Observations</td>
<td>35016</td>
<td>35016</td>
<td>35016</td>
<td>35016</td>
</tr>
</tbody>
</table>

* : p (MWU) < 0.01
Table 1.6: Decomposition of Forward Premium Changes (2012-2015). This table presents the decomposition of forward price premium changes with a 20% wind generation increase (~800MW) into impacts from increase in volatility, forecast errors, and wind generation without any change in the other two factors. Forecast errors and wind generation itself increase the premium, while volatility has relatively small impacts on the prices and does not make any statistically significant changes. A remarkable pattern observed is that only wind itself produces some heterogeneous responses across the different sizes of firms, which is quite reasonable because both volatility and forecast errors are exogenous without regard to firm sizes because they are simply driven by variable weather.

<table>
<thead>
<tr>
<th></th>
<th>Volatility</th>
<th>Forecast Errors</th>
<th>Wind Only</th>
<th>ALL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dominant</td>
<td>-0.04</td>
<td>0.14*</td>
<td>0.28**</td>
<td>0.36**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Fringe</td>
<td>-0.04</td>
<td>0.14**</td>
<td>0.16**</td>
<td>0.25**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Observations</td>
<td>35016</td>
<td>35016</td>
<td>35016</td>
<td>35016</td>
</tr>
</tbody>
</table>

* : p (MWW) < 0.01,  + : p (SR) < 0.01
Table 1.7: Decomposition of Firms’ Strategy Changes by Wind Factors. This table shows firms’ strategic responses (the fraction of quantities sold in the day-ahead market) to the three factors incorporated in the 10-30% wind generation increase (400MW~1200MW on average) and characterize the impacts by three factors: volatility, forecast errors, and wind generation itself. Two different types of firms show heterogeneous responses: Most importantly, with increased wind generation only, dominant and fringe firms move in opposite directions. While dominant firms withhold sales in the day-ahead market to engage in intertemporal price discrimination, fringe firms increase their fractions of sales in the day-ahead market. In addition, with the increase in forecast errors, the day-ahead market fractions for both types have increased.

<table>
<thead>
<tr>
<th></th>
<th>10% Increase</th>
<th>20% Increase</th>
<th>30% Increase</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10% Increase</td>
<td>20% Increase</td>
<td>30% Increase</td>
</tr>
<tr>
<td>Dominant</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volatility</td>
<td>-0.07</td>
<td>-0.14</td>
<td>-0.21*</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Forecast Errors</td>
<td>0.18</td>
<td>0.36*</td>
<td>0.55*</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Wind Only</td>
<td>-0.09</td>
<td>-0.20*</td>
<td>-0.31*</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.005)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>ALL</td>
<td>0.02</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Fringe</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volatility</td>
<td>0.03</td>
<td>0.05</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Forecast Errors</td>
<td>0.13</td>
<td>0.25*</td>
<td>0.38*</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Wind Only</td>
<td>0.26</td>
<td>0.51*</td>
<td>0.77*</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.007)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>ALL</td>
<td>0.41*</td>
<td>0.81*</td>
<td>1.21*</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.008)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Observations</td>
<td>35016</td>
<td>35016</td>
<td>35016</td>
</tr>
</tbody>
</table>

* : \( p \) (MWU) < 0.01
Figure 1.1-1: Price Discrimination by Residual Monopolist. This figure indicates the intuition behind the declining prices in sequential markets. As a residual monopolist participates in both forward and spot markets, the spot market price ($p_2$) is the opportunity costs of selling products in the forward markets. The monopolist withholds a quantity and sells $q_1$. In the spot market, the monopolist has an incentive to sell additional quantity $(q_2 - q_1)$ because the lower price in the second market would not affect the price charged in the first market.
Figure 1.1-2: Price Discrimination by Residual Monopolist with Wind Generation. These figures show the changes in production strategies of a residual monopolist caused by integrating wind generation into sequential markets. The upper panel indicates a residual demand shift by the wind generation if all the generation was sold by forward market. The bottom panel shows the case in which all the wind generation was sold through spot market.
Figure 1.2-1: Hourly Average of Forward Price Premium (All). This figure presents the hourly average of the forward price premium (blue line) at all fossil-fueled resource nodes from 2011 to 2016. Shaded areas represent the 25th and 75th percentiles. A total of 365,197 observations are used to find a mean value for each hour (8,764,728 observations in total).
Figure 1.2-2: Hourly Average of Forward Price Premium (Seasonal). This figure presents the hourly average of the forward price premium at all fossil fueled resource nodes from 2011 to 2016 during shoulder months (blue line and shades) and summer (orange line and shades). Each shaded area represents the 25th and 75th percentiles. Shoulder months are defined as March, April, May, October, and November, when there is relatively high wind generation while electricity demand is low. High net load months are defined as June to September, when there is high electricity demand with relatively low wind generation.
Figure 1.2-3: Hourly Average of Forward Price Premium and AS Prices. These figures show strong correlations between forward price premiums and ancillary service prices. Because selling electricity in day-ahead market is an opportunity cost of selling capacities to the ancillary service market, they are highly correlated. Shoulder months (Low) are defined as March, April, May, October, and November, when there is relatively high wind generation while electricity demand is low. High net load months (High) are defined as June to September, when there is high electricity demand with relatively low wind generation.
Figure 1.3: Wind Generation Cleared at Day-ahead Market. This figure shows average quantities of wind generation cleared in the day-ahead market. Despite an 83% increase in installed wind capacity in the ERCOT from 2011 to 2015, wind generation sold in the day-ahead market remains almost the same.
Figure 1.4: Hourly Mean and 95% CI of Wind Generation in ERCOT. These figures show the hourly means of wind generation in 2011 (blue dotted line) and 2015 (orange dotted line) during shoulder months (upper panel) and summer (lower panel). Error bars show 95% confidence intervals. As wind generation increases, the fluctuations in wind generation have remarkably increased and caused more volatile market supplies.
Figure 1.5: Wind Generation Forecast Errors. This figure shows wind forecast errors over actual wind generation (MWh). Wind forecast errors are defined as ‘the realized wind generation in the real-time market minus the forecasted wind generation in the day-ahead market’. Several patterns are shown in the figure: 1) As the amount of realized wind generation increases, forecast errors have increased (more dispersed errors in the right part of the figure). 2) There is an increasing trend of the forecast errors, which indicates that when realized wind is low, the value is more likely to be less than the forecasted values, and thus the mean values of the forecast errors are negative. When actual wind generation is high, it is more likely that the value is greater than the expected one, and thus the forecast errors are positive. Generally, one can see that the wind generation forecasts are biased.
Figure 1.6-1: Regression of Prediction Results on Actual Targets – Dominant Firms. These figures present overall prediction accuracies for prediction models that have been trained without a held-out test sample (2015) and used to predict the outputs with the uncontaminated covariates by closed-loop predictions. If the overall shapes of scattered points resemble the shape of a line with slope of 1 (predicted and actual outputs become closer), it would demonstrate that the prediction models perform better.
Figure 1.6-2: Prediction Errors for Day-Ahead and Real-Time Market Prices (July). These figures show samples of predicted time paths for the day-ahead and the real-time prices that have been trained without a test sample (year 2015 data) and used to predict the outputs with the uncontaminated covariates by closed-loop predictions. Upper pairs, which consist of the comparison of outputs with targets and time series for prediction errors, show the results for the day-ahead market prices. Lower pairs show the results for the real-time market prices. The results are for July.
Figure 1.7: Counterfactual 20% Increase in Wind Generation. An upper panel of these figures shows an average counterfactual wind path that replicates wind generation with 20% increased wind capacities based on actual data from 2012 to 2015. For the upper panel, the blue dotted line shows the mean values of actual hourly wind generation and the red dotted line denotes a counterfactual path. A lower panel shows the difference between the actual and the counterfactual paths. Error bars show 95% confidence intervals.
Figure 1.8: Counterfactual 20% Increase in Wind Generation – Volatility and Uncertainty. These figures present the counterfactual changes in volatility (upper panel) and forecast errors (lower panel) driven by a 20% wind generation increase (~ 800MW). Volatility is measured by hourly standard deviations of 15-minute wind generation. Forecast errors are calculated by the actual wind generation committed in the real-time market minus the forecasted wind generation in the day-ahead market. Blue dotted lines show the average values of the business-as-usual setting (actual data) and red dotted lines show the counterfactual settings. Error bars show 95% confidence intervals.
Figure 1.9: Forward Price Premium Changes (2012-2015) with 20% Wind Increase. These figures present average hourly forward price premium changes over 2012-2015, caused by a 20% increase in wind generation (~ 800MW). Dotted lines show the average values and shaded areas denote 95% confidence intervals for the point estimates. The confidence interval has been estimated by a bootstrap method with 100,000 samplings.
Figure 1.10: Firms’ Strategic Responses to Increased Wind Generation. This figure presents 4-year average changes in the fractions (%) of the quantities sold in the day-ahead market with respect to the total commitments in the real-time market. Thicker lines denote the results with higher wind generation. As wind generation increases, heterogeneous strategic responses of firms have been observed: the dominant firms withhold more quantities from the forward market while the fringe firms sell more through the day-ahead market to exploit the increases in price differences generated by wind change.
Figure 1.11: Decomposition of Forward Premium Changes with 20% Wind Increase. These figures show the results for decomposing forward price premium (FPP) changes—induced by 20% wind generation increase (~ 800MW)—into three factors: From the top, volatility, forecast uncertainty, and wind generation itself. A volatility increase produces price spikes in the real-time market during peak hours and somewhat decreases an FPP during those hours. Forecast errors increase overall FPP. Wind generation itself drives most of the FPP changes. It is important to note that the heterogeneity of the FPP between dominant and fringe firms arises from changes in wind generation only (bottom panel).
These figures show the results for firms’ strategic responses to three factors accompanied by 20% wind generation increases (~ 800MW). The numbers on the y-axis show the ratio (%) of the quantities sold in the day-ahead market to the total commitments in the real-time market. When volatility increases (top panel), the dominant firms slightly decrease the ratio while the fringe firms increase it. With the forecast error increase, both types of firms increase the ratios while the extent of that increase for dominant firms is generally larger. The most remarkable heterogeneous responses are observed in the bottom panel: with the changes, they clearly move in opposite directions.

**Figure 1.12:** Decomposition of Firms’ Strategic Responses to Wind Generation Increase.
Figure 1.13: Forward Price Premiums and Firms’ Withholding Sales in the Forward Market. These figures highlight the forward price premium differences between dominant and fringe firms (upper panel) and the heterogeneous responses (%) of two types of firms (bottom panel), driven by 30% increase (~ 1200MW) in wind generation with fixed two other adverse factors. The two panels clearly show that when dominant firms withhold sales in the day-ahead market (from approximately 6 a.m. to 8 p.m.), the forward price premium differences between the dominant and the fringe firms arise. In other words, during those times, the two types of firms take opposite strategies. All 10-30% increases in ‘wind generation only’ produce the same patterns.
Chapter 2

Adaptive Resistance Management with Uncertain Fitness Costs

2.1. Introduction

Pesticides, antibiotics, and antimicrobials (collectively referred to as *biocides*) are essential for the economic control of biological systems. Yet, in nearly every case of biocides being widely applied, selection for resistance in the target organism inevitably follows. The depletable aspect of biocide susceptibility has led resource economists to analyze the intertemporal tradeoffs surrounding resistance in a range of cases, including agricultural pests (Miranowski and Carlson 1986; Laxminarayan and Simpson 2002), disease vectors (Brown, Dickinson, and Kramer 2013; Kim et al. 2016), and pathogen resistance to antibiotics and antimicrobial compounds (Herrmann and Gaudet 2009; Laxminarayan 2004). One basic insight from this literature is that biocide susceptibility may be viewed as renewable or nonrenewable, depending on the biological conditions specific to a given application. Consequent lessons from resource economics, including the delineation of market failures, the application of capital theory to these resource stocks, and prescriptions for corrective incentives for resource users, can then be applied on this basis.
However, a fundamental difference in the bioeconomics of resistance vis-à-vis other natural resources is uncertainty regarding renewability. The classic harvest-based examples of renewable resources, such as fisheries harvesting and forest rotation, are observably renewable (even if their exact rate of recharge is uncertain), and the same holds for the classic nonrenewable resources: fossil fuels, minerals, and old-growth forests (when considered on human timescales). Yet in the case of resistance, it is often unclear whether biocide susceptibility can recharge and, if it can, at what rate. Answering this question is necessary for efficient management, and is an important precursor to the prescription of corrective economic incentives.

This paper applies an adaptive management (AM) framework to investigate the role of uncertain renewability in biocide susceptibility and resistance dynamics. While other research has proposed qualitative heuristics for managing pesticide resistance using AM concepts (e.g. Downes et al. 2010), this is the first formal bioeconomic analysis of adaptive resistance management (in any context, not just pesticides). Our methodology combines a standard biological model of insecticide resistance, extended to include stochastic shocks and an uncertain biological parameter governing renewability, with a dynamic economic optimization model allowing for the dynamic learning about the uncertain parameter.

To illustrate its application, we examine a mathematical AM approach to managing resistance to transgenic crops containing insecticidal *Bacillus thuringiensis* (Bt) genes, where much of the underlying biology of resistance – in particular, the renewability of Bt susceptibility – remains uncertain (Gassmann, Carrière, and Tabashnik 2008). However, because our model is a novel combination of generic components, it is sufficiently flexible to be applied directly to other cases of insecticide resistance and can provide insight into AM modeling for biocide resistance in other organisms, such as microbes or plants. We discuss these extensions at the end of the paper.

The biological parameters governing the renewability of biocide susceptibility are generally referred to as fitness costs. These are costs in the evolutionary sense, not an economic one. Fitness costs capture any evolutionary disadvantage resistant organisms possess relative to
susceptible organisms. Examples may include an insect pest in which insecticide-resistant genotypes lay fewer eggs or develop more slowly than the wild types (Carrière et al. 1994; Gassmann, Carrière, and Tabashnik 2008). Or, in the case of antibiotic resistance, bacteria with resistance genes may have reduced motility or cellular function than wild types (Melnyk, Wong, and Kassen 2014). When biocide use is widespread, the advantage of the resistance trait outweighs associated fitness costs, so that the resistant organisms outcompete susceptible types. When biocides are absent, however, the presence of fitness costs implies that susceptible organisms outcompete resistant types. This logic leads to the expectation that susceptibility recharges in the population when fitness costs are present, but not in their absence. Despite their obvious importance for resistance management, fitness costs are often poorly understood and highly uncertain in many contexts.

The uncertainty and relevance of the fitness costs of Bt resistance provide an instructive example. Concerns about resistance to Bt have existed for as long as these tools have been used, in part informed by decades of experience with the evolution of resistance to traditional chemical insecticides. In the 1990s, the U.S. Environmental Protection Agency (EPA) instituted a mandate that corn and cotton growers plant a percentage of their fields as non-Bt “refuges,” in order to sustain susceptible, wild-type populations of pests. Bourguet et al. (2000) review this policy, referring to it as “the most impressive mandatory [insect resistance management] system ever developed” (pp. 210). The exact requirements for refuge structure and size were developed by a scientific advisory panel convened by the EPA. Recommendations were based on biomathematical models of population genetics similar to the type used in this paper (EPA 2000). However, the EPA acknowledges in this document significant uncertainty in the underlying biology of Bt resistance, including fitness costs, and that better information would improve policy. Other research confirms that fitness costs may arise through diverse mechanisms (Gassmann, Carrière, and Tabashnik 2008), but the existing research usually stops short of providing a net magnitude of resistance spread and subsidence that could be used in modeling, at least over the timescales that are economically relevant for resistance management.
Economic modeling of resistance dynamics can be useful for policy analysis for at least two reasons: One is the evaluation of intertemporal tradeoffs between using a highly effective biocide now versus saving it to ensure its future effectiveness. This aspect of the decision problem has been previously addressed in prior bioeconomic work (Livingston, Carlson, and Fackler 2004; Laxminarayan and Simpson 2002), which has generally shown for example that Bt refuge sizes should be smaller than those recommended based on purely biomathematical modeling (such as the mandates used by the EPA). However, this paper highlights another motivation for economic modeling by explicitly considering uncertainty in the decision problem. In the case of resistance, this uncertainty is inseparable from the intertemporal dynamics of resistance evolution, since for example any given refuge policy will over time reveal some information about the underlying fitness costs. This is the motivation for our AM approach.

A couple of novel findings emerge from our analysis. First, on the methodological side, we demonstrate that the intuitive formulation of the general biological model admits the use of conjugate priors in characterizing fitness cost uncertainty. This puts this model among a rare number of cases in the adaptive management literature (among those, the seminal work of Walters 1986) admitting the use of conjugate priors. Most current research on AM utilizes numerical dimension reduction techniques in belief updating, such as density projection (Springborn and Sanchirico 2013), which is computationally costly and can introduce additional computational error. As with the classic models by Walters et al., conjugacy in our context is provided by the fact that our dynamic model of resistance selection can be viewed as type of Kalman filter. Thus, another way to view the contribution of this paper is the application of dynamic optimization using Kalman filters to economically relevant models of population genetics.

Another analytical contribution we believe novel in the AM literature is the use of information from multiple, continuous state variables to maximize the efficiency of Bayesian-belief updating. In our model, we can consistently infer fitness costs using only information on the change in resistance levels in the population. However, the variance of the posterior
distribution can be further reduced by including a statistic derived from the other state variable: population density. In fact, the variance-minimizing combination of these two sources of information turns out to be a weighted average of their respective statistics, using the correlation between the random components of the system as the optimal weight. This can be interpreted as a Bayesian generalized least squares (GLS) estimation of a two-equation model.

Finally, in simulation analysis of our Bt refuge application, we find that under some conditions an active AM (AAM) regime can perform significantly better than a passive AM (PAM) regime in resistance management. AAM incorporates the value of policy experimentation into dynamic optimization, whereas PAM updates beliefs but without factoring the marginal value of learning into management decisions. AAM generally poses greater computational challenges in dynamic optimization than PAM. Prior research in other applications (Walters 1986; Rout, Hauser, and Possingham 2009; Bond and Loomis 2009; Springborn and Sanchirico 2013) has found relatively little gain in value from AAM over PAM, calling into question whether the additional computational burden of AAM is warranted. However, in our application, we find that under some initial conditions AAM can perform significantly better than PAM. In our baseline scenario, the value of information (VOI) from AAM is 36% higher than the VOI from PAM in a case where resistance is high and we have virtually no information about fitness costs. This VOI difference climbs as high as 62% in other parameter specifications. The difference in the AAM and PAM regimes derives from a more restrained use of Bt being optimal under AAM. Such restraint appears to generate more useful information about uncertain fitness costs, likely because more restrained biocide use after a period of sustained application is one of the clearest ways to learn about fitness costs.

The remainder of this paper is structured as follows: The next section describes the model, first presenting the biological model with uncertain fitness costs using a conjugate prior. The modeling section also presents the dynamic optimization framework and defines our economic performance metrics in terms of the ‘value of information’ (VOI). The third section describes our application to Bt resistance management, first presenting the data and
parameterization of the model and numerical solution method and then turning to the numerical results. The last section discusses the broader implications of our findings.

2.2. Model

In this section, we first present a stochastic model of resistance evolution with uncertain fitness costs and Bayesian belief updating. We then describe dynamic economic optimization and adaptive management of this model.

2.2.1. A Stochastic Biological Model of Resistance Evolution

We adapt a standard model of discrete-time, stochastic population dynamics and pesticide resistance in an arthropod pest with uncertain fitness costs (Hofbauer and Sigmund 1998; Hartl and Clark 1997). The model is formulated in discrete-time in order to facilitate Bayesian updating, and a Ricker model of density dependence is employed, with random environmental shocks to the population growth rates.

Pesticide resistance is assumed to be conferred by a single gene mutation, with two alleles. The original, wild-type allele $S$ of the gene results in pesticide susceptibility, whereas the mutated $R$ allele confers resistance. The arthropod population is assumed be diploid (two sets of chromosomes), meaning that there are three genotypes to account for in the population: two homozygote types ($RR$ and $SS$) and a heterozygote type ($RS$). Define $N^g_t$ as the density of the pest subpopulation of genotype $g \in \{RR, RS, SS\}$ at time $t$. The populations evolve according to 

\[ N^g_{t+1} = \exp\{r(1 - N_t/K)\} W^g_t N^g_t, \]

where $W^g_t$ is the fitness of subpopulation $g$ at time $t$ and $N_t := \sum_g N^g_t$. The term $\exp\{r(1 - N_t/K)\}$ reflects a Ricker model of density dependence, where $K > 0$ is a density-dependence parameter (equivalent to carrying capacity in a deterministic setting) and where $r > 0$ is an intrinsic growth parameter. In our model, we define the genotype fitnesses as:

\[ W_t^{SS} := \exp\{-q_t \mu + \epsilon_t\} \]  

(2.1)
\[ W_t^{RR} := \exp\{-\lambda + \nu_t\} \]
\[ W_t^{RS} := h W_t^{RR} + (1 - h) W_t^{SS} \]

where \( \mu > 0 \) is a parameter determining the mortality impacts on homozygote susceptibles of a given level of pesticide application, defined by \( q_t \geq 0 \), and \( h \) determines the relative dominance of the resistance gene in heterozygotes (e.g. with \( h = 1 \) resulting in a fully dominant resistance gene and \( h = 0 \) resulting in a fully recessive gene). The parameter \( \lambda \) is the fitness cost of the resistant homozygote, and will be discussed in detail below. Finally, \( \epsilon_t \) and \( \nu_t \) are environmental shocks respectively for the homozygote susceptible and resistant types which are distributed normally, each with mean zero and a variance of \( \sigma^2 \).\(^1\) Note that \( W_t^g \) expresses the reproductive fitness of genotype \( g \) at time \( t \) relative to the median fitness of the SS type in the absence of pesticide application, which can be seen by evaluating \( W_t^{SS} \) at \( \epsilon_t = 0 \) (the median shock) and \( q_t = 0 \) (no pesticide application) which yields \( W_t^{SS}|_{(\epsilon_t=0,q_t=0)} = 1 \). We also assume that \( \text{corr}(\epsilon_t, \nu_t) = \rho \), allowing for the environmental shocks to the susceptible and resistant populations to be correlated (but not perfectly so).

### 2.2.1.1. Reduction to a Two-dimensional Dynamical System

It is standard practice in bioeconomic models of resistance to reduce the dimensionality of the biological model using equilibrium concepts from population genetics (Laxminarayan and Simpson 2002; Grimsrud and Huffaker 2006; Brown, Dickinson, and Kramer 2013). In our discrete-time model, dimension-reduction proceeds as follows: Given the population \( N_t^g \) density of each genotype \( g \) at time \( t \), the proportion of \( R \) genes in the total number of \( R \) and \( S \) alleles on all chromosomes in the population is \( p_t := \frac{2N_t^{RR} + N_t^{RS}}{2N_t^{RR} + N_t^{RS} + 2N_t^{SS}} \). Since we are assuming diploid

---

\(^1\) An alternative approach to modeling stochastic population genetics is to treat individual organisms discretely, with random mating. This produces the Fisher-Wright model of genetic drift (Hartl and Clark 1997). Such models have been used in adaptive control of resistance in small-population contexts, e.g. within-host evolution of resistance to HIV and cancer therapies (Fischer, Vázquez-Garcia, and Mustonen 2015). However, this form of stochasticity is only relevant for small populations: as the population becomes larger, the dynamics converge to a conventional deterministic model due precisely to the Central Limit Theorem. Introducing environmental shocks as we do here allows for stochastic behavior in large populations (which is demonstrable for a variety of pest species, e.g. Hutchison et al. 2010).
organisms, the $RR$ genotype contributes two $R$ genes per organism, the $RS$ genotype contributes one $R$ gene and one $S$ gene, and the $SS$ genotype contributes two $S$ genes. Assuming random mating among the different genotypes, and that the Hardy-Weinberg equilibrium conditions hold, the proportions of each genotype $RR$, $RS$, and $SS$ are given, respectively, by $p^2_t, 2p_t(1 - p_t)$ and $(1 - p_t)^2$. Given large populations and sufficient mixing, these equilibrium assumptions are innocuous (Hartl and Clark 1997). Their utility is that they allow us to express the biological model as a two-state dynamical stochastic system, expressed in terms of the total pest population density $N_t$ and the frequency of the resistant gene mutation $p_t$:

$$N_{t+1} = N_t \cdot \exp \left\{ r \left( 1 - \frac{N_t}{K} \right) \right\} \cdot \frac{\bar{W}_t}{[W_t^{RR}p_t^2 + W_t^{RS}2p_t(1-p_t) + W_t^{SS}(1-p_t)^2]}$$

$$p_{t+1} = \frac{W_t^{RR}p_t^2 + \frac{1}{2}W_t^{RS}2p_t(1-p_t)}{W_t^{RR}p_t^2 + W_t^{RS}2p_t(1-p_t) + W_t^{SS}(1-p_t)^2} \cdot \frac{\bar{W}_t}{\bar{W}_t^R} \cdot p_t$$

The intuition behind these equations is first that the total population grows according to a Ricker model, with a density-dependent growth rate given by $\exp \left\{ r \left( 1 - \frac{N_t}{K} \right) \right\}$, adjusted for the mean fitness $\bar{W}_t$ of the population at that point in time. This mean fitness is dynamically dependent on the stochastic shocks $\epsilon_t$ and $\nu_t$, the level of pesticide use $q_t$, as well as the prevalence $p_t$ of the resistance gene, which evolves according to the second equation in (2). This amounts to a standard discrete time replicator equation (Hofbauer and Sigmund 1998): The numerator in this equation is the mean relative fitness $\bar{W}_t^R$ of the $R$ allele multiplied by the relative frequency $p_t$ of the $R$ allele, accounting for homozygotes and heterozygotes, and the denominator is the mean relative fitness $\bar{W}_t$ of the total population. When the mean fitness of the $R$ allele is greater than the mean fitness of the total population ($\bar{W}_t^R > \bar{W}_t$), then this allele is increasing in frequency ($p_{t+1} > p_t$).
2.2.1.2. Dynamic Behavior

A few key properties of the dynamic system in (2) that are relevant for the present analysis. The supplementary material presents additional analytic details of equilibrium behavior of the system. First, it is worth noting the equilibria of the deterministic special case of this system, i.e. when $\sigma^2 = 0$. In this case it can be verified using (1) and (2) there exists a threshold level of pesticide coverage $q^* = \frac{\lambda}{\mu}$, such that if pesticide applications are sustained above this threshold ($q_\infty > q^*$), then the population will become fully resistant in the long-run ($p_\infty = 1$). If pesticide applications are below this threshold in the long-run, then the population will tend towards full susceptibility (i.e. $q_\infty < q^*$ implies that $p_\infty = 0$).\(^2\) When applications are sustained at the threshold level ($q_\infty = q^*$), then a continuum of steady states are supported for $p_\infty \in [0,1]$. One important implication of this steady state analysis in the deterministic case is that non-negligible fitness costs $\lambda > 0$ yield benefits, even once we have selected for a fully resistant population, since densities are lower than the fully susceptible carrying capacity: Sustained selection for resistant pests with a positive fitness cost leads to replacement of the population with a less fit genotype and hence lower densities.

These qualitative equilibrium properties are preserved when stochasticity is permitted ($\sigma^2 > 0$). The supplementary material provides an analytic characterization of the stochastic system’s equilibrium behavior. Here, we simply demonstrate through simulation the behavior of the stochastic system with fixed $q$ in Figures 2.1. When pesticide coverage exceeds the threshold, $q > q^*$, the population becomes fully resistant, and vice versa when $q < q^*$ (Figure 2.1). We can also see that when initial resistance is high, the ability to recharge susceptibility through the cessation of pesticide use depends on the presence of fitness costs $\lambda$ (Figure 2.1).

One key feature of the stochastic system, particularly for the purposes of the Bayesian analysis that follows, is that the correlation $\rho$ between the stochastic shocks $\epsilon_t$ and $\nu_t$ completely determines whether $p_t$ behaves stochastically or not. Figure 2.3 shows that when $|\rho|$ increases

\(^2\) The use of $\infty$ as a subscript here is the usual short-hand for $\lim_{t \to \infty} x_t$, i.e. a steady state of a dynamic variable $x_t$. For the bivariate biological system analyzed here, with exogenous $q_\infty$, it is straightforward to verify that there exists a unique steady state for $N$ and $p$, except in the singular case of $q_\infty = q^*$. 
towards one, the dynamics of $p_t$ become more deterministic. As the supplementary material shows, when $|\rho| = 1$ the dynamics of $p_t$ become completely deterministic for $|\rho| = 1$, even though the dynamics of $N_t$ remain stochastic for $\sigma^2 > 0$. The is because when $|\rho| = 1$, the relative fitness of each of the genotypes is constant (even if absolute fitness is stochastic), meaning that their densities change in synchrony so that their frequencies remain constant. This is analytically shown in the following section on Bayesian inference.

2.2.1.3. Bayesian Inference

In general, the biological model at the beginning of Section 2.2.1 can be viewed as a three-dimensional constrained quasi-Kalman filter, because the homozygote SS and RR population densities are log-linear in the control $q$, Gaussian noise $(\epsilon_t, \nu_t)$ and the unknown parameter $\lambda$. The ‘constrained, quasi-’ qualification comes from the fact that the heterozygote RS genotype is restricted to a Hardy-Weinberg mixture of the homozygote populations, both in terms of their genotype frequency ($2p_t(1 - p_t)$) and their genetic fitness ($W_t^{RS} = hW_t^{RR} + (1 - h)W_t^{SS}$). The fact that these mixtures are arithmetic instead of geometric eliminates exact log-linearity of the heterozygote population dynamics.³

These features of the biological model, in conjunction with our aim of keeping the dimension of the state space tractable, lead us to focus specifically on the two-dimensional model in (2) and a single uncertain parameter: the fitness cost $\lambda$ controlling the renewal of pesticide susceptibility. In this case, we can still use a normal conjugate prior to obtain a closed-form posterior distribution for $\lambda$. The relative fitness between the SS and RR genotypes at any given point in time is log-linear in the control, fitness cost and noise:

$$\omega_t := \frac{W_t^{SS}}{W_t^{RR}} = \exp\{-q_t\mu + \lambda + \epsilon_t - \nu_t\}$$

³ This issue could be partially resolved by formulating heterozygote dominance geometrically instead of arithmetically, e.g. $\tilde{W}_t^{RS} = (W_t^{RR})^{\beta}(W_t^{SS})^{1-\beta}$, in which case log $\tilde{W}_t^{RS}$ is Gaussian. However, this is a nonstandard formulation in the population genetics literature, and even if this reformulation is introduced the arithmetic Hardy-Weinberg mixture defining the RS genotype frequency still remains.
Rewriting the dynamic equation for \( p_{t+1} \) in (2) in terms of \( \omega_t \) yields:
\[
p_{t+1} = \frac{p_t^2 + [h + (1-h)\omega_t]p_t(1-p_t)}{p_t^2 + [h + (1-h)\omega_t]2p_t(1-p_t) + \omega_t(1-p_t)^2}
\] (2.4)

Solving this equation for \( \omega_t \) yields an expression for imputed relative fitness \( \hat{\omega}(p_{t+1}, p_t) \) as a function of observed current and next-period gene frequencies \( p_t, p_{t+1} \), which we denote as the function:
\[
\hat{\omega}(p_{t+1}, p_t) := \frac{p_t^2(1-p_{t+1}) + hp_t(1-p_t)(1-2p_{t+1})}{(1-h)2p_t(1-p_t) + (1-p_t)^2[p_{t+1} - (1-h)(1-p_t)p_t]}
\] (2.5)

The utility of this function is that, given observed levels of resistance \( p_t \) and \( p_{t+1} \) in the current and next periods, we can directly impute the relative fitness between the \( RR \) and \( SS \) genotypes. This provides a data-point for Bayesian inference. Taking the natural logarithm of (3) and (5) and combining, we obtain \( \log \hat{\omega}(p_{t+1}, p_t) = -q_t\mu + \lambda_t + \epsilon_t - \nu_t \) and define the statistic \( \eta_{t+1} := \log \hat{\omega}(p_{t+1}, p_t) + q_t\mu \). Given the joint normal distribution for \( (\epsilon_t, \nu_t) \), we obtain a marginal distribution for the observed data, conditional on the uncertain fitness cost \( \lambda \):
\[
\eta_{t+1} | \lambda \sim \mathcal{N}\{\lambda, 2\sigma^2(1-\rho)\}
\] (2.6)

Given the above marginal likelihood with known \( \sigma^2 \) and \( \rho \), the conjugate prior distribution for \( \lambda \) is \( \lambda \sim \mathcal{N}\left\{\theta_t, \frac{2\sigma^2(1-\rho)}{\gamma_t}\right\} \), where \( \theta_t \) is the current mean estimate of \( \lambda \) and \( \gamma_t \) is the accumulated sample size (number of observations) gathered over time. \( \theta_t \) and \( \gamma_t \) are our two belief state variables that will be used in adaptive management.

We could use (2.4) – (2.6) to update beliefs with the usual Bayesian updating formulas for Gaussian models: \( \theta_{t+1} = (\gamma_t \hat{\theta}_t, \frac{2\sigma^2(1-\rho)}{\gamma_{t+1}}) \) and \( \gamma_{t+1} = \gamma_t + 1 \). Such belief dynamics are consistent, in that \( \lim_{t \to \infty} \theta_t = \lambda \). However, eq. (2.5) in particular only uses information about the state transition for the resistant gene frequency, \( p_t \), and ignores information in the state transition of overall population densities, \( N_t \). Using only the gene frequency information therefore can be interpreted as Bayesian estimation of a single-equation ordinary least squares (OLS) regression (in this case, with a single parameter: \( \lambda \)).
Yet we can obtain further information from the other state variable of this model, \( N_t \). This information can be viewed as comprising an additional, correlated equation for regression analysis. In such multiple-equation models, generalized least squares (GLS) regression, which transforms the regression data using the cross-equation error variance matrix, is more efficient than OLS (Wooldridge 2010). We use the same approach here. First, to get the additional ‘regression’ equation, we solve the \( N_{t+1} \) recursion in (2) in terms of \( W_t RR \). This yields the following function for imputing the absolute fitness of the \( RR \) homozygote, which is determined by \( \lambda \):

\[
\hat{W}_t^{RR} [N_{t+1}, N_t, p_t, \hat{\omega}] := \frac{N_{t+1}}{N_t} \cdot \exp \left\{ -r \left( 1 - \frac{N_t}{K} \right) \right\} \cdot \left[ p_t^2 + [h + (1 - h)\hat{\omega}]2p_t(1 - p_t) + \hat{\omega}(1 - p_t)^2 \right]^{-1}
\]

By substituting (2.5) into (2.8) for \( \hat{\omega} \), we obtain the following statistic:

\[
\psi_{t+1} := -\log \hat{W}_t^{RR} [N_{t+1}, N_t, p_t, \hat{\omega}(p_{t+1}, p_t)] = \lambda - \nu_t
\]

Because \( W_t^{RR} = \exp\{-\lambda + \nu_t\} \), this statistic is marginally distributed \( \psi_{t+1} | \lambda \sim \mathcal{N} \{\lambda, \sigma^2\} \). Moreover, \( \eta_{t+1} \) and \( \psi_{t+1} \) are jointly normally distributed, with

\[
\text{cov}(\eta_{t+1}, \psi_{t+1} | \lambda) = \sigma^2(1 - \rho).
\]

To increase efficiency of the \( \lambda \) estimator, we can use an optimally weighted linear combination of \( \eta_{t+1} \) and \( \psi_{t+1} \): \[a \eta_{t+1} + (1 - a) \psi_{t+1}\]. This statistic is itself normally distributed and, conditional on \( \lambda \), has expected value \( \lambda \) for any weight \( a \). One can check that the optimal weight minimizing the variance of this linear combination is \( a = \rho \), yielding

\[
\text{Var}[\rho \eta_{t+1} + (1 - \rho) \psi_{t+1}] = \sigma^2(1 - \rho^2).
\]

This optimal weighting is conceptually the same as GLS. The efficient, full-information statistic we therefore use to update beliefs is:

\[
\chi_{t+1} := \rho \eta_{t+1} + (1 - \rho) \psi_{t+1} | \lambda \sim \mathcal{N} [\lambda, \sigma^2(1 - \rho^2)]
\]

Applying the standard conjugacy formulas for the normal distribution, we obtain the following dynamics for beliefs regarding the fitness cost:

\[
\theta_{t+1} = \left( \frac{\gamma_t}{\gamma_t + 1} \right) \theta_t + \left( \frac{1}{\gamma_t + 1} \right) \chi_{t+1}
\]
\[ \gamma_{t+1} = \gamma_t + 1 \]

such that at any time \( t \) fitness cost beliefs are characterized by \( \lambda \sim \mathcal{N} \left( \theta_t, \frac{\sigma^2 (1-\rho^2)}{\gamma_t} \right) \). These formulas show the standard Bayesian principle of placing increasing weight on prior beliefs \( \theta_t \), given a larger accumulated sample size \( \gamma_t \), i.e. \( \lim_{\gamma_t \to \infty} \theta_{t+1} = \theta_t \).

### 2.2.2. Dynamic Optimization and Adaptive Management

To simplify notation, define the vector of biological state variables as \( x := (N, p) \). In general, the economic objective we consider is to choose the level of pesticide use in each period so as to maximize the expected present value payoff over an infinite time horizon with a per-period discount factor of \( \beta \in (0,1) \). Let \( \pi(q, x) \) denote current-period payoff as a function of the current level of pesticide application \( q \) and the state of the pest biology \( x \).

Similar to other adaptive management studies (Springborn and Sanchirico 2013), we compare four types of optimization problems. The standard stochastic dynamic program (SDP) assumes a known fitness cost \( \lambda \). The ‘active’ adaptive management (AAM) program assumes an uncertain \( \lambda \), with belief updating built into all parts of the dynamic program. The ‘passive’ adaptive management (PAM) program excludes belief updating from the optimization but includes it in policy implementation and simulation. Finally, the no-learning model (NLM) assumes an uncertain \( \lambda \), but without any belief updating.

The SDP treats the fitness cost \( \lambda \) as perfectly known. Mathematically, our objective in this case is to obtain a feedback policy function \( q_{\lambda}^{SDP}(x) \) and the associated expected net present value function \( V_{\lambda}^{SDP}(x) \) with an infinite time horizon. These functions are defined as:

\[
q_{\lambda}^{SDP}(x_0) := \arg \max_{q_{\lambda}(\cdot) \in Q} \mathbb{E} \left\{ \sum_{t=0}^{\infty} \beta^t \pi[q_{\lambda}(x_t), x_t] \right\} \lambda \]

\[
V_{\lambda}^{SDP}(x_0) := \mathbb{E} \left\{ \sum_{t=0}^{\infty} \beta^t \pi[q_{\lambda}^{SDP}(x_t), x_t] \right\} x_0, \lambda \}
\]
where \( Q \) is a constraint space of feasible pesticide application feedback functions. We explicitly subscript and condition the above by \( \lambda \) due to our particular interest in this parameter for adaptive management. For the remainder of the paper, we generally include variables that are explicitly treated dynamically as function arguments in parentheses – in the above, \( x \) – from variables which are treated as fixed, which are subscripted (\( \lambda \) in the above).

Because our biological model is a Markov process and our time horizon infinite, this problem can be solved using a stationary Bellman equation. We change notation from using \( t \) subscripts for the state variables to using prime notation so that \( x' \) is next period’s (uncertain) biological state. The Bellman equation is:

\[
V^\text{SDP} (\lambda)(x) = \max_{q \in Q} \left\{ \pi(q, x) + \beta \mathbb{E}_x \left[ V^\text{SDP} (\lambda)(x')|q, x, \lambda \right] \right\} \tag{2.13}
\]

where \( Q \) is the feasible set of pesticide application levels and the random variables \( N' \) and \( p' \) are determined according to the stochastic dynamics in (2.2), conditional on known \( q, N, p \) and \( \lambda \).

We contrast the SDP solution to (2.9) with an AAM program with unknown \( \lambda \) and beliefs about this parameter updated according to (2.8). The AAM value function \( V^\text{AAM} (N, p, \theta, \gamma) \) satisfies the following Bellman equation:

\[
V^\text{AAM} (x, \theta, \gamma) = \max_{q \in Q} \left\{ \pi(q, x) + \beta \mathbb{E}_{x', \theta'} \left[ V^\text{AAM} (x', \theta', \gamma')|q, x, \theta, \gamma \right] \right\} \tag{2.14}
\]

which now includes \( \theta \) and \( \gamma \) as state variables, defining the prior and (when updated to \( \theta' \) and \( \gamma' \) according to eq. 2.8) the posterior belief distributions of \( \lambda \). Note that the next period mean estimate \( \theta' \) is stochastic, because as seen in (2.8) it depends on the known current-period control level \( q \), known current resistance \( p \), and unknown next-period resistance \( p' \). (The other next-period belief state \( \gamma' \) just increments the accumulated sample size and is hence deterministic.) The AAM program explicitly accounts for belief uncertainty via the expectation operator \( \mathbb{E}_{x', \theta'} [-] \) in (2.10), which now accounts for the uncertain next-period belief \( \theta' \) rather than a known fitness cost \( \lambda \). Thus the optimal AAM feedback rule accounts for the effects of current pesticide decisions, not only on next-period expected pest damages and resistance levels, but also
on how our current actions may provide information to improve subsequent control decisions. In this sense such an adaptive management program is ‘active,’ because it allows for policy experimentation that seeks information that may improve subsequent decisions. This ‘probing’ feature of AAM is its fundamental characteristic (Walters 1986).

Intuitively, the AAM program will yield lower ex ante expected value relative to the SDP with a known fitness cost, since the latter represents a case of perfect information about $\lambda$. In contrast, we would expect the AAM program to perform better than a passive adaptive management (PAM) program, as well as a non-learning model (NLM) with the same initial beliefs about fitness costs. The policy functions for both the PAM and NLM cases solve the same Bellman equation:

$$V_{\theta,\gamma}(x) = \max_{q \in Q} \left\{ \pi(q, x) + \beta \mathbb{E}_{x'} \left[ V_{\theta,\gamma}(x') \mid q, x, \theta, \gamma \right] \right\}$$

This value function $V_{\theta,\gamma}(x)$ is characterized by an assumption of fixed beliefs, i.e. belief updating is not captured in the $\mathbb{E}_N \cdot \cdot \cdot$ operator in (2.11). Let the $\tilde{q}_{\theta,\gamma}(x)$ be the policy function that solves the maximization problem in (2.15). Then the PAM value function is:

$$V_{PAM}^{PAM}(x_0, \theta_0, \gamma_0) := \mathbb{E} \left[ \sum_{t=0}^{\infty} \beta^t \pi \left[ \tilde{q}_{\theta_t,\gamma_t}(x_t), x_t \right] \right] x_0, \theta_0, \gamma_0$$

The indexing of the beliefs $\theta_t, \gamma_t$ by $t$ shows how the PAM policy passively updates beliefs using (2.8), but does not allow for information probing as AAM does. In contrast, the NLM model has the following value function:

$$V_{\theta,\gamma}^{NLM}(x_0) := \mathbb{E} \left[ \sum_{t=0}^{\infty} \beta^t \pi \left[ \tilde{q}_{\theta,\gamma}(x_t), x_t \right] \right] x_0, \theta, \gamma$$

These definitions emphasize the difference between the two cases by subscripting the NLM value function by fixed beliefs $\theta$ and $\gamma$ in (2.13), whereas they are included as dynamic function arguments in the PAM program, even though their dynamics are not explicitly accounted for in the Bellman equation in (2.15) as they are by the AAM program in (2.14).

In the VOI literature (e.g. Yokota and Thompson 2004), the gain in ex ante expected value from the uninformed and perfectly informed cases is defined as the ‘expected value of
perfect information’ (EVPI). Here, the SDP and NLM are the most- and least-informed cases respectively so that $\text{EVPI}_{\theta, \gamma}(x) := \mathbb{E}_x[V^\text{SDP}_A(x)|\theta, \gamma] - V^\text{NLM}_A$. Similarly, we evaluate the VOI associated with AAM and PAM as the ex ante expected gain in value of these respective regimes over the NLM; these gains are bounded from above by the EVPI (Walters 1986).

### 2.3. Application to Adaptive Management of Bt Refuge Policy

We apply the above framework to the case of Bt crops and refuge policies for forestalling resistance. To focus on the adaptive management component of this problem, we consider a simple formulation of the economic objective, abstracting from a number of other agricultural input and pest management decisions. The control in this case is defined as the fraction $q \in Q := [0,1]$ of cropped area planted to the Bt variety, and the remaining fraction $(1 - q)$ planted to the conventional variety, i.e. refuge. We assume that the area planted to refuge is subject to a proportional pest damage of $\Phi(N)$, where $\Phi(\cdot)$ is a continuous, differentiable damage function with $\Phi' > 0$, $\Phi(0) = 0$ and $\lim_{N \to \infty} \Phi(N) \leq 1$. The area planted with Bt is subject to damage only from resistant organisms and partial damage from partially resistant heterozygotes, with proportional damage of $\Phi(N^R + hN^{RS})$. Given a crop yield of $\bar{Y}$ units per hectare in the absence of the pest, a crop price of $P$ per unit, and a price premium (technology fee) of $w$ per hectare’s worth of seed for the Bt variety, current value average profit per hectare $\pi$ is:

$$
(q, N, p) := P\bar{Y} \left( q \frac{(1 - \Phi[N[p^2 + h2p(1 - p)]])}{\text{proportional yield on Bt area}} + (1 - q) \frac{(1 - \Phi(N))}{\text{proportional yield on non-Bt area}} \right) - wq \quad (2.18)
$$

To parameterize our model, we use data from Hutchison et al. (2010) on damages and larval densities for the European corn borer (ECB) in the midwestern US, as well as costs of Bt

---

4 This assumption that the Bt variety contemporaneously protects against pest damage from susceptible organisms is consistent with previous bioeconomic models developed by Livingston et al. (2004), Grimsrud and Huffaker (2006), and Qiao et al. (2008), but not with Laxminarayan and Simpson (2002). Our formulation is also consistent with the entomological-agronomic evidence in the case of European corn borer (the pest considered in our application).

5 We assume a constant seeding density here for simplicity.
seed. Bt corn is among the most economically important genetically engineered crops globally (NASEM 2016), and ECB has historically been the most economically significant pest controlled by Bt corn in the US. While Bt resistance has not yet been observed in economically relevant levels in ECB populations, there are at least six published cases of field resistance of ECB to Bt, three of them within the last seven years (ARPD 2016). The EPA’s (time-invariant) refuge mandate for corn requires growers to plant at least 20% with non-Bt corn seed (Bourguet, Desquilbet, and Lemarié 2005). As described in more detail in the supplementary material, we use Hutchison et al.’s data on ECB larval densities, associated yield losses and price information to parameterize the population biology model and the profit function in (2.18). Table 2.1 reports the parameterization used in our simulations.

We present the results of our application by first comparing the optimal policy functions in the state space, and then compare the ex ante expected values between the SDP, AAM, PAM and NLM programs via Monte Carlo simulation with a variety of initial conditions. We solve value functions in (2.13) to (2.17) using function approximation combined with the standard contraction mapping algorithm for Bellman equations (Miranda and Fackler 2004). We use a linear function approximant with a total of 196,992 collocation nodes for the four state variables, and 512 quadrature nodes for the two, correlated environmental shocks and the uncertain fitness cost. For a given parameter set, the algorithm for the AAM case optimizing over all four state variables took less than a week to converge on a PC with 10-core 3.4 GHz processor and 40 GB of memory.

2.3.1. Feedback Policy Functions

Figures 2.4-2.6 show the optimal Bt levels for AAM, PAM/NLM and the difference between them. Each plot in these figures represents the optimal Bt level over the biological state space \((N,p)\), conditional on a belief state \((\theta,\gamma)\). The columns of plots in each of these figures span different values for beliefs about the expected fitness cost \(\theta\), and the rows span different accumulated sample sizes \(\gamma\) reflecting varying levels of certainty. The top row of both Figure 2.4
and Figure 2.5 shows the SDP policy function for a perfectly known fitness cost. As must be the case in both of these figures, we see the adaptive management policy functions appear to converge to the SDP as we scan from the bottom to the top rows, reflecting increasingly certain beliefs about fitness costs.

We are not aware of previous bioeconomic research on pesticide resistance which explicitly analyzes feedback control for a stochastic system (as opposed to optimal control in a deterministic setting), and so we first discuss some general patterns in the feedback control. Most of these plots reveal a nearly discontinuous control, in which optimal Bt use tends to be either zero or a hundred percent. This reflects the fact that the reward function in our application to Bt is linear in the control, according to (2.18). In fact, previous optimal control models of Bt resistance have shown continuous-time versions of this model without stochasticity to imply a singular, ‘bang-bang’ optimal control (e.g. Laxminarayan and Simpson 2002). While the stochasticity of our model and its nonlinear discrete-time biological dynamics do not yield a fully singular control problem (a fact which facilitates numerical computation), there are only small regions of the state space in which an interior Bt level is optimal.

Given this approximately bang-bang nature of the optimal feedback control, it appears that we can further characterize this control in most cases by a threshold level of resistance \( p^*(N) \), varying across pest density \( N \), such that when \( p \ll p^*(N) \) it is optimal to fully utilize Bt, and when \( p \gg p^*(N) \) it is optimal to plant 100% refuge. In general across all of the plots, pest densities near their natural ‘median carrying capacity’ of \( K = 101 \) larvae per plant support the greatest extent of refuge planting, with full refuge being optimal for resistance allele frequencies above 40% (i.e. \( p^*(101) \approx 0.4 \)). The only consistent exception to this rule is the fact that no Bt planting is optimal when pest densities are near zero, reflecting the trivial case in which the small damage from low pest levels is outweighed by the price premium for Bt technology. When pest densities are far above their median carrying capacity of 101 (scenarios relevant to consider because of the right-skewing of our lognormal processes), it is almost always optimal to plant 100% Bt. In these cases, the expediency of reducing overwhelming pest damages in the near-
term significantly outweighs the marginal value of preserving future Bt susceptibility. This is true until resistance virtually fixates with \( p \rightarrow 1 \), at which point the Bt technology becomes essentially useless.

For both the AAM and PAM cases, greater uncertainty regarding fitness costs enlarges the area of the biological state space in which maximal Bt use is optimal. The bottom rows of Figure 2.4 and 2.5 represent a case of a nearly diffuse prior for fitness costs, with an accumulated sample size of \( \gamma = 0.1 \) (intended to approximate \( \gamma = 0 \)). For example, at an expected value of \( \theta = 0.3 \) the 95% confidence interval for \( \lambda \) for this level of uncertainty is approximately \([-2.9, 3.5]\).\(^6\) It appears that the predominant effect of such uncertainty about fitness costs is therefore to tilt Bt usage towards the present, hastening the evolution of resistance regardless of the expected fitness cost. As information is accumulated about fitness costs, the area in which refuge is optimal grows. The extent of this growth depends on current expectations about fitness costs, as well as on whether an AAM or PAM is being used.

The main difference between AAM and PAM is that the PAM policy is much more aggressive in its Bt use. Figure 2.6 most clearly shows this difference, by plotting the difference between the AAM and PAM policy functions with the dark areas indicating the PAM policy’s Bt use exceeding the AAM policy’s. The approximately singular nature of the control means that the difference is nearly binary: The dark areas of the plots are mostly those in which PAM Bt use is maximal and AAM Bt use is absent. Since both policies converge to the SDP as information accumulates, the differences between them diminish with increasing certainty about \( \lambda \).

### 2.3.2. Case Study Simulations

To further investigate the dynamics implied by adaptive management of resistance, we use the policy feedback functions above to simulate biological and economic outcomes for four cases that we imagine to be of practical relevance for managers (Table 2.2). Each case corresponds to a

\(^6\) Negative fitness costs are mathematically and biologically feasible in the above models, just unlikely in standard contexts. Similarly to the unlikeliness of dollar bills lying on sidewalks, negative fitness costs beg the question of why resistance did not originally prevail in the wild.
set of initial conditions in which we imagine prior biocide use having led to varying levels of resistance and pest pressure, but in which adaptive management has not yet been used. Case $N_H p_L$ depicts a naïve system as it might appear at the introduction of Bt, with high levels of pest density and low levels of resistance. Due to Bt’s efficacy, pest densities are likely to fall rapidly after deployment of the technology but with resistance still low (Hutchison et al. 2010; Grimsrud and Huffaker 2006). This leads to case $N_L p_L$, which might also depict a situation in which the pest population has been controlled quickly early on with the biocide, but where resistance has started to emerge. As Bt resistance emerges and evolves, the pest population begins to rebound (assuming other effective controls are not available—an issue we take up at the end). This situation is depicted by case $N_M p_M$, with medium levels of pest densities and resistance. Finally, after persistent Bt use, the population eventually becomes fully resistant and densities rebound, at which point costly use of Bt would likely be abandoned and—depending on fitness costs—resistance may eventually recede, possibly allowing for this process to repeat itself. Adaptive management may be introduced at any point in this cycle (potentially averting full resistance), and so we simulate the biology and management regimes and calculate the VOI for each of these cases.

For each case, we simulate a large number of joint draws for the series of shocks ${\epsilon_t, \nu_t}_{t=0,\ldots,T}$ and the fitness cost parameter $\lambda$, with the shocks distributed jointly normal as described in Section 2.2 and $\lambda$ distributed ex ante as a uniform random variable on the interval $[0, r]$. This rules out biologically unlikely cases, in which the resistant type is absolutely more fit than the susceptible type ($\lambda < 0$), even in the absence of the biocide (begging the question of why the resistant type did not initially dominate the wild-type population) or in which the fitness cost is so high that a fully resistant pest population would go extinct ($\lambda > r \Rightarrow N_\infty = 0 | p_\infty = 1$). In all cases, we initialize beliefs as a diffuse prior, with $\theta_0 = r/2$ and $\gamma_0 = 0.1$. In each case,
we simulate for 50 years outcomes under the four alternative management regimes described in Section 2.2.2: SDP, AAM, PAM and NLM.⁷

Results from these case-study simulations are presented in Figures 2.7-2.9. Figure 2.7 presents mean time paths for resistance levels (allele frequency). Figure 2.8 presents mean time paths for the control, i.e. Bt usage and refuge levels. Figure 2.9 presents the VOI for the different regimes.⁸

When resistance is initially very low, information about fitness costs (the SDP, AAM, and PAM regimes) does not lead to substantive differences in resistance, relative to the NLM (averaging across simulation draws). In contrast, with medium-to-high initial levels of resistance, the AM and SDP regimes manage Bt more conservatively, resulting in long-run resistance levels lower than the NLM. In the case where resistance is very high \( N_H p_H \), differences in resistance between the regimes emerge the earliest, suggesting greater differences in economic performance (due to discounting) in this case. These patterns are mirrored in Figure 2.8’s plots of mean optimal biocide usage over time. In cases where differences emerge, Bt use in NLM is generally greater than in the AM or SDP regimes.

Figure 2.9 shows how the passive and active AM regimes perform as measured by their ability to approach the EVPI: the maximal gain that could be achieved through perfect knowledge of \( \lambda \). The first pattern to note from this figure is that the EVPI declines as resistance increases. The intuition for this pattern is that, as resistance increases, the potential actions for effectively reacting to better information to manage resistance become more limited. However, the VOI for AM appears to increase with resistance, both in absolute terms and as a percentage.

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⁷ A uniform \textit{ex ante} distribution for \( \lambda \) over \([0, r]\) can be approximated by a normal distribution with mean \( r/2 \) a large variance (small \( \gamma \)), i.e. a diffuse prior – which is what we consider in our simulations. However, analytical belief updating using normal conjugate priors with support of \( \lambda \in (-\infty, \infty) \) does not permit truncation, depicting a decision maker who ignores this information about bounds on \( \lambda \). In practice, this bounding does not have too appear to be practically significant for adaptive management, as beliefs converge early to lie within these bounds. Any costs from ignoring this information on \( \lambda \) bounds appears to be outweighed by the advantages of having conjugate priors.

⁸ We also examined the mean time paths for pest density, but these showed few clear differences between regimes, were less insightful, and so omitted for concision.
of the EVPI. At medium levels of resistance (case $N_M p_M$), the VOI for active regime is nearly a third of the EVPI; at high levels of resistance this fraction reaches 71%. What explains this countervailing pattern between the EVPI and the VOI for the AM regimes? Logically, the answer to this question must relate to learning: In the EVPI, perfect certainty precludes further learning. The VOI patterns in the AM regimes evidently reflect a greater difficulty in learning about fitness costs at low levels of resistance. This conclusion agrees with intuition: An intuitive way to infer fitness costs is by observing declines in resistance in the absence of biocide use. However, if there is little resistance to observe to begin with, such inference becomes more difficult.

Figure 2.9 also shows that the larger the VOI in adaptive management generally is, the larger the gap between AAM and PAM. For low levels of resistance, the VOI for AAM and PAM are virtually indistinguishable. But the gap between AAM and PAM grows with increasing levels of resistance, with the active VOI exceeding the passive VOI by 3% in case $N_M p_M$ and then by 36% in case $N_H p_H$. This again is intuitive: as opportunities for learning grow, so does the potential to exploit these opportunities in dynamic optimization.

In the supplementary material, we conduct sensitivity analysis with respect to the correlation parameter $\rho$, to investigate the robustness of the patterns described here. While the correlation parameter does affect the magnitudes of the VOI (with lower $\rho$ associated with higher EVPI and lower VOI from AM), the qualitative patterns are surprisingly robust: EVPI decreases with higher resistance, the VOIs for both AAM and PAM increase and the gap between the VOI for AAM and PAM grows. In the most extreme scenario analyzed ($\rho = 0.25$), the VOI for AAM is 21% higher than in PAM in case $N_M p_M$, and 62% higher in case $N_H p_H$.

### 2.4. Discussion

Resistance to pesticides and other biocides has been increasing in economic importance, as agricultural and human health systems have become reliant on biochemical control. Yet
significant uncertainty pervades the biomathematical models that often serve as the basis for existing resistance management (e.g. Bt refuge policies). Our contribution in this paper is to demonstrate a tractable bioeconomic approach for quantitative adaptive management of resistance.

Perhaps the most useful result from our analysis is that a standard biological model of diploid resistance with Gaussian environmental shocks behaves approximately like a Kalman filter and admits the use of conjugate prior density functions in Bayesian analysis of fitness costs. This fact greatly facilitates dynamic optimization in adaptive management, permitting a number of methodological and applied extensions in future applications.

Indeed, our general model should be directly and rapidly extendable to other cases of pesticide resistance characterized by a single genetic mutation conferring resistance to pesticides relying on a single mode of action, in which case the control $q$ at any point in time would embody exposure of the pest population to all biochemicals using the same mode of action (IRAC 2017). Given data similar to that employed for ECB in this paper, the model could be directly applied to other economically relevant agricultural pests. Diamond-back moth (*Plutella xylostella*), a major pest of cruciferous vegetables, is known for its ability to rapidly evolve insecticide resistance: There are over 862 published cases of insecticide resistance (ARPD 2016). The corn rootworms (*Diabrotica*) provide another example in which Bt resistance has potentially evolved to economically relevant levels (Gassmann et al. 2014).

Adaptive resistance management is also highly relevant for public health applications. The most direct applications of the present model would involve management of insecticide resistance in mosquito vectors of malaria, dengue and other human pathogens, which is a growing concern (Ranson and Lissenden 2016) and in which fitness costs are known to play an important role (Brown, Dickinson, and Kramer 2013; Kim et al. 2016; Hancock et al. 2016). The general approach here may also be used to develop quantitative methods for adaptive resistance management of antibiotics and other drugs for treating transmissible human pathogens, systems
in which research has also demonstrated the importance and uncertainty regarding fitness costs

A number of important extensions of this approach could be relevant for adaptive
resistance management. First, allowing for multiple gene loci conferring resistance to multiple
biochemical modes of action would extend the realism and applicability of the model. Multiple,
interacting and compensatory resistance genes are possible in many contexts. While such
extensions would increase computational complexity of dynamic optimization in ways that may
suffer from the ‘Curse of Dimensionality,’ the analytical conjugate priors for a vector of fitness
costs across loci would likely persist with additional dimensions, allowing for more tractable
analysis than would be the case with approximation methods like density projection (Springborn
and Sanchirico 2013; Maclachlan, Springborn, and Fackler 2016).

Other relevant extensions of the model could explore how expansion of the action space
affects the VOI yielded from adaptive resistance management. Mathematically, the VOI is
necessarily non-decreasing with the size of the action space: More management tools proffer
more ways of responding to better information. Other actions could consist of non-pesticidal pest
control methods, as part of an integrated pest management (IPM) portfolio. For example, Kim et
al. (2016) include larviciding as an additional mosquito control method which serves essentially
as a ‘backstop’ technology to conventional insecticide-based, resistance-inducing control. And
Downes et al. (2010) describe a number of AM-motivated approaches for managing Bt resistance
in Australian cotton systems, including time-varying refuges (as studied here), late-season
application of other pesticides and controlled use of multiple (a.k.a. ‘stacked’) Bt genes inserted
into a single plant variety.

Additional actions could also include even more ‘active learning,’ such as direct
experimentation to identify fitness costs and other aspects of evolutionary dynamics. This could
involve targeted lab and field trials with different time-varying levels of biocide use. Such
analysis, coupled with information on research costs, could allow estimation of the economic
value of applied research into different facets influencing resistance dynamics (e.g. Kim et al. 2016).

Related to the possible extension of allowing active experimentation in the model, spatial considerations also warrant future analysis. While some research has examined bioeconomic interactions among neighboring growers drawing on the same pool of pesticide susceptibility (Ambec and Desquilbet 2012), there are specific implications for spatial considerations with respect to uncertainty and adaptive management. At a basic level, independence of environmental shocks over space can be leveraged to improve statistical inference (and is a basic principle justifying crop insurance). With respect to adaptive management, the present model characterizes the policy maker as conducting one grand experiment, and does not consider independent, simultaneous experimentation over smaller areas. To the extent that results from such small-scale experiments could be extrapolated over wider areas – with more heterogeneous environments – such independent experimentation could improve efficiency of information acquisition. These types of spatial considerations in adaptive management have rarely been considered, and point to an area ripe for future research.
### Table 2.1: Model Parameters for Bt Refuge Application.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value (units)</th>
<th>Notes and source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intrinsic growth rate ($r$)</td>
<td>0.791 (rate per year)</td>
<td>Estimated from data in Hutchison et al. (2010)</td>
</tr>
<tr>
<td>Density-dependence parameter ($K$)</td>
<td>101 larvae per plant</td>
<td>Estimated from data in Hutchison et al. (2010)</td>
</tr>
<tr>
<td>Bt efficacy ($\mu$)</td>
<td>2.28 (rate per year)</td>
<td>Estimated from data in Hutchison et al. (2010)</td>
</tr>
<tr>
<td>Variance in population shocks ($\sigma^2$)</td>
<td>0.577 (rate per year squared)</td>
<td>Estimated from data in Hutchison et al. (2010)</td>
</tr>
<tr>
<td>Correlation in subpop. shocks ($\rho$)</td>
<td>0.5</td>
<td>Assumed and checked in sensitivity analysis</td>
</tr>
<tr>
<td>Dominance of resistant gene ($h$)</td>
<td>0</td>
<td>Based on literature (Gassmann, Carrière, and Tabashnik 2008)</td>
</tr>
<tr>
<td>Fitness cost ($\lambda$)</td>
<td>[0, 0.6] (rate per year)</td>
<td>Gassmann et al. (2008). Note: $\lambda &lt; r$ for resistant population to be viable.</td>
</tr>
<tr>
<td>Relative yield loss function ($\Phi(N)$)</td>
<td>$\Phi(N) \approx 0.00783 \cdot N^{0.456}$ + 0.00482 $\cdot N^{0.142}$</td>
<td>Estimated from data in Hutchison et al. (2010)</td>
</tr>
<tr>
<td>Corn price ($P$)</td>
<td>$100 per Mg</td>
<td>Assumption in Hutchison et al. (2010)</td>
</tr>
<tr>
<td>Max yield ($\bar{Y}$)</td>
<td>12 Mg per hectare</td>
<td>Assumption in Hutchison et al. (2010)</td>
</tr>
<tr>
<td>Bt seed price premium / technology fee ($w$)</td>
<td>$17.5 per hectare</td>
<td>Assumption in Hutchison et al. (2010)</td>
</tr>
</tbody>
</table>

See supplementary materials for additional details on this parameterization.
Table 2.2: Description of Simulation Case Studies.

<table>
<thead>
<tr>
<th>Case Label: Description</th>
<th>Initial pest density, $N_0$ (% of wild carrying capacity)</th>
<th>Initial resistance, $p_0$ (resistant allele frequency)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_H p_L$: High pest density &amp; low resistance</td>
<td>100%</td>
<td>1%</td>
</tr>
<tr>
<td>$N_L p_L$: Low pest density &amp; low resistance</td>
<td>10%</td>
<td>10%</td>
</tr>
<tr>
<td>$N_M p_M$: Medium pest density &amp; medium resistance</td>
<td>60%</td>
<td>20%</td>
</tr>
<tr>
<td>$N_H p_H$: High pest density &amp; high resistance</td>
<td>99%</td>
<td>99%</td>
</tr>
</tbody>
</table>
Figure 2.1: Simulation with High, Constant Pesticide Coverage ($q_T \gg \lambda/\mu$). Other parameters for this simulation based on Table 1.
Figure 2.2: Simulation with Cessation of Previously High Pesticide Coverage ($q_t \gg \lambda/\mu$ for $t < 2020$, and $q_t = 0$ for $t > 2020$). Other parameters for this simulation based on Table 1.
Figure 2.3: Effects of Environmental Shock Correlation $\rho$ on Resistance Dynamics (with cessation of pesticide, $q_t \gg \lambda/\mu$ for $t < 2020$, and $q_t = 0$ for $t > 2020$). Other parameters for this simulation based on Table 1.
Figure 2.4: Optimal Active Adaptive Management Policy Feedback Function. Top row SDP is the stochastic dynamic program policy function for known fitness cost $\lambda$. Lighter areas indicate greater Bt use (smaller refuge).
Figure 2.5: Optimal Feedback Policy Functions for Passive Adaptive Management and Non-Learning Model. Top row SDP is the stochastic dynamic program policy function for known fitness cost $\lambda$. Lighter areas indicate greater Bt use (smaller refuge).
Figure 2.6: Difference between Optimal Feedback Policy Functions for PAM versus AAM. Dark areas indicate Bt use in PAM greater than (refuge less than) AAM. Solid line vertical on each plot indicates steady state median pest density in absence of resistance.
Figure 2.7: Mean Resistance Prevalence Trajectories across Management Regimes. SDP = Stochastic Dynamic Program, AAM = Active Adaptive Management, PAM = Passive Adaptive Management, NLM = Nonlearning Model. Mean trajectories computed from 10,000 simulations.
Figure 2.8: Mean Levels of Bt Usage across Management Regimes. See Fig. 7 caption.
**Figure 2.9:** Value of Information across Management Regimes for selected case studies. See Figure 7 caption.
Chapter 3

Diagnosis of Market Symptoms by Artificial Intelligence: A Case Study of Changing Market Integration in Electricity Market

3.1. Introduction

Short-term wholesale electricity markets differ from markets for other products because the electricity produced by a generation unit at one location should be delivered to others simultaneously via transmission lines with limited capacity. The transmission network capacity often restricts the amount of energy generation units can provide at certain locations and the amount consumers at certain locations can withdraw (Wolak, 2011), a phenomenon known as transmission congestion. A dramatic increase in renewable energy generation units in the U.S. has raised concerns about transmission capacity constraints because generation units tend to be clustered in locations far from the population center where most demand occurs.¹

Given these circumstances, investment in transmission infrastructure has increased across the entire country, reaching $21 billion in 2016 (U.S. EIA, 2018). For example, the Midcontinent

¹ Volumetric-based subsidies, such as the production tax credit for renewable energy generation, may skew wind investment towards high-producing sites with lower covariance in their variable output with market prices. Furthermore, because wind production depresses prices, this bias has been linked to covariance between wind sites (Schneider & Roozbehani, 2017).
Independent System Operator’s Multi-Value Portfolio includes $6.6 billion for 17 transmission projects designed to provide greater access to renewable energy resources, namely wind and Canadian hydro. Energy Gate is a $6 billion major transmission program from the Western Electricity Coordinating Council that aims to expand access to wind and solar generation units. The Public Utility Commission of Texas, which oversees the electricity sector of Texas having large wind generation, has established several transmission projects to transmit wind power from remote parts of Texas (primarily west Texas) to more heavily populated areas. This expansion is collectively referred to as Competitive Renewable Energy Zones (CREZ).

This paper presents a case study that measures the impact of the $6.9 billion portfolio of CREZ projects on the Texas wholesale electricity market (i.e., Electric Reliability Council of Texas [ERCOT]). The study uses a method based on artificial intelligence to manage a vast amount of data in a complex, grid-based market system. With Texas being the last in 2010, U.S. wholesale electricity markets have switched from integrated market-clearing designs with zonal pricing to disaggregated nodal-pricing designs in which each location in a regional market can be cleared at a different price. This change is based on the premise that the nodal market can precisely respect the configuration of the transmission network in the dispatch and pricing process (Wolak, 2011). In economic research on the disaggregated market structure, granular prices provide more detailed information than aggregated prices. For example, nodal prices can reflect either correlation or discontinuity between small regions, present a more accurate picture of the extent of the market, determine instances of market power by firms, and identify localized transmission congestion. The latter is especially important in the electricity market, as such congestion could potentially reverse entire market outcomes. However, extracting comprehensive information from several hundreds to thousands of different nodal prices without losing critical details remains challenging.

This paper presents a novel empirical method, a self-organizing map (SOM), to gather valuable information from large dimensions of market outcomes for economic analysis. SOM is a type of machine learning algorithm used to draw inferences from datasets consisting of input
data without labeled responses. In the context of this study, SOM first learns how prices in different locations and various times are grouped into the same topological space and then automatically classifies millions of market-clearing prices into countable categories. By discovering intrinsic patterns within 201 nodal market prices that clear ERCOT every hour, the method formalizes discrete dependent variables reflecting hourly market conditions into a time-series format. Additionally, this paper investigates how the CREZ project and a surge of wind generation units have collectively shifted from one to other classified market conditions.

The first part of this paper describes the SOM method in detail. Hourly data with different nodal prices from 2011–2016 are respectively categorized into eight and 11 classes for the sake of simplicity. Different classes comprise different market conditions ranging from no price difference throughout the region to overall price spikes. The SOM method also clusters the hours for similar types of localized symptoms (e.g., price spikes in west Texas, price spikes in south Texas, and negative prices in west Texas). This study demonstrates heterogeneities among classes using summary statistics, a time trend for each class, topological graphics of clustering results, and contour surface maps of price distribution over the ERCOT region representing each class.

The second part of this paper uses multinominal logistic regression to analyze the interactive effects of CREZ projects and the dramatic increase in wind generation on market conditions. The study uses hourly wind generation, hourly zonal load data, the daily ratio between natural gas prices and coal prices sold to ERCOT power plants, and the daily proportion of CREZ project completion. The projects initiated since 2008, including 186 completed projects in which 3,589 miles of transmission lines were constructed through November 2014 following rapid progress in 2013 (Figure 3.7 depicts the rapid increase). Wind generation units installed in ERCOT also increased by 84% between 2011–2016 (Potomac Economics, 2016). The exogenous variation in CREZ and hourly wind generation allows for identification of the effects of these changes on market outcomes.
The empirical results validate the SOM classification and indicate that CREZ has substantially decreased price discrepancies over ERCOT. For instance, wind-related negative real-time electricity prices in west Texas have declined by 15% as CREZ projects have enabled wind power to flow to more areas with electricity demand. Similarly, price spikes in west Texas have fallen by 11% as CREZ has facilitated electricity imports from fossil fuel units located outside west Texas when wind generation declines in the west.

By contrast, increased wind generation reduces the likelihood of market conditions with no congestion by 2.7% while increasing the chance of negative prices in west Texas by 5.4%, suggesting that excessive wind generation creates electricity surplus in the western part of the state. Furthermore, the results clearly demonstrate a negative relationship between wind generation and the likelihood of market conditions reflecting price spikes in west Texas, which is to be expected as high price conditions in west Texas are likely when wind generation declines rapidly. In cases of lower wind generation, other dispatchable units should ramp up to satisfy market demand in west Texas. Occasionally, a large fluctuation in wind generation requires the starting-up of fossil fuel power plants that cost thousands of dollars.

In Houston, price spikes were found to be 25% more likely following CREZ projects. As the market becomes more integrated with CREZ, high prices in west Texas from a temporary decline in wind generation have attracted more generation units that previously tended to supply electricity only to Houston prior to CREZ. That is, even if low electricity prices from wind generation in west Texas help to reduce prices in other ERCOT regions after CREZ projects, the adverse impacts of intermittent wind generation also permeate other regions.

More importantly, given that the installed wind capacity in ERCOT is expected to increase by another 63% from 2016–2020, the extent to which $6.9 billion in CREZ projects and increased wind generation has affected market conditions, along with how CREZ effectiveness will be maintained under varying degrees of wind generation, warrants consideration. Empirical results indicate that CREZ completion increases the probability of normal conditions, particularly when wind generation is high (i.e., greater than 10 GW), implying that ERCOT can
efficiently incorporate high levels of wind generation with CREZ. CREZ can also facilitate wind
generation exports from west Texas, especially in instances of high wind generation, whereas
imports of electricity generated outside west Texas increase when wind generation declines.
Furthermore, on average, the adverse effects of wind generation nearly disappear after CREZ
project completion. However, a more detailed examination reveals that extreme wind generation
(whether low or high) can still exacerbate ERCOT market conditions.

This paper is closely related to several recent studies. LaRiviere and Lu (2018)
investigated the impacts of transmission expansion in the Texas electricity market on price
differentials between wind-generation centers in West ERCOT and load centers in North
ERCOT, South ERCOT, and Houston ERCOT (Figure 3.1). They carried out one-to-one
comparisons of average zonal prices before and after the transmission expansion project and
conducted a welfare analysis based on changes in zonal price differences. While their findings
were informative, the present study takes a different approach and demonstrates a universal
method for a price dispersion analysis in electricity markets: it employs disaggregated nodal
prices, uses a data-driven method to classify market conditions from a broader market
perspective, and examines how the interaction of wind generation and transmission line
development contributes to different market conditions. The wind generators in ERCOT were
accidently clustered in a market segment (west Texas) used in the former market structure and
the impacts of transmission expansion on market price dispersions can be measured through the
average zonal market price differentials for this case study, even if the analysis still could not
detect the localized transmission congestions. However, an analysis of other electricity wholesale
markets should require a method to both timely and regionally classify market conditions from
hundreds to thousands of nodal market outcomes.

A second, distinct study considers the environmental impacts of transmission line
expansion through increased wind generation trade in a population center (Fell, Kaffine, and
Novan, 2018). They identified how wind generation replaces different types of fossil fuel
generators in different locations, which contributes to heterogeneous environmental damage
across regions; however, their work was less focused on market outcomes associated with expansion.

Another line of research has applied hierarchical clustering analysis to categorize electricity market nodes based on their price correlations to define the unknown extent of a nodal market (Mercadal, 2016). In this type of market, it is challenging to correctly measure residual demand for each market agent because the market extent varies across the market footprint over time. By using the estimated market extent and residual demand, Mercadal (2016) employed a structural model to study firms’ bidding behaviors, whereas the current study clusters temporal market conditions holistically to determine how improved market connectivity might inform overall market conditions.

The remainder of this paper is organized as follows. Section 3.2 describes the study context and data used for analysis. Section 3.3 outlines the SOM method and empirical framework using multinomial logistic regression. Section 3.4 presents the empirical results and relevant implications, and Section 3.5 concludes this study.

3.2. Context and Data

3.2.1. Nodal Market

In a nodal market structure, the energy market is organized as an auction in which participants submit bids to buy or sell energy in particular locations. The ERCOT then clears the market by solving a linear programming problem that minimizes cost subject to capacity constraints imposed by the transmission network. Because the network has limited capacity, electricity supplied in different locations is not a homogeneous good. Therefore, the cost of an MWh and the willingness to pay for it each vary across the market footprint, and the way in which the market has been cleared is not always apparent.

The locational marginal pricing (LMP) establishes a price per MWh at a given network node based on the marginal cost of delivering the next MW to that node. LMP remains the same
throughout the market in the event of no congestion. If congestion exists, however, then LMP will differ from node to node. ERCOT’s market-clearing process involves an integrated day-ahead forward market and a real-time imbalance market. This paper uses real-time market prices calculated as the sum of LMP and reserve price adders\(^2\), including 201 different settlement point prices per hour. The points on the map in Figure 3.1 indicate the approximate locations of transmission nodes.

### 3.2.2. CREZ and Wind Generation

CREZ projects are primarily designed to move electricity generated from a renewable energy source (mostly wind) from remote parts of Texas (i.e., west Texas and the Texas Panhandle) to more heavily populated areas such as Austin, Dallas-Fort Worth, and San Antonio (Figure 3.2). ERCOT initiated projects in 2008 and went on to spend $6.9 billion completing 186 projects involving the construction of 3,589 miles of transmission lines through November 2014. CREZ transmission projects will eventually transmit approximately 18,500 MW of wind power.

ERCOT’s installed wind generation capacity also increased by 84% from 2011–2016. Wind plants can offer power at low prices because they essentially have zero marginal costs in contrast to fossil fuel plants. Furthermore, due to the revenue stream resulting from the production tax credit (PTC, which generates tax benefits whenever wind generates electricity) and payments from the state’s renewable portfolio, wind plants can offer electricity at negative prices. In particular, volumetric-based subsidies such as PTC may bias wind investments towards high-producing sites, thereby creating clusters of wind generators in remote areas (Schneider & Roozbehani, 2017). As such, when wind generation exceeds transmission constraints, west Texas will likely have negative prices because wind generation in the area cannot spread to other

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\(^2\) ERCOT offers two types of reserve prices as incentives to ensure that sufficient energy generation resources will be online: 1) ancillary service prices and quantities competitively procured by bids from firms in the day-ahead market; and 2) reserve price adders calculated based on the operating reserve demand curve (ORDC). ERCOT implemented an ORDC to reflect the inverse relationship between the reserve price adder and the currently available system-wide reserve on June 1, 2014, precisely representing an actual price change for the Ancillary Service Imbalance. (Potomac Economics, 2016)
regions. West Texas is also likely to experience more price spikes than other regions because a high number of zero-marginal-cost wind generators can drive all marginal fossil fuel generators off the margin. Once wind generation drops, lower-cost fossil fuel generators cannot ramp up quickly enough to compensate for lost wind generation; therefore, they must instead activate high-cost generators temporarily.

3.2.3. Data

The empirical study in this paper was conducted using data from two sources: publicly available datasets on ERCOT’s website (http://www.ercot.com); and the energy data service company ABB, from which real-time nodal market prices were gathered. The CREZ construction report was obtained from ERCOT upon request, as were hourly wind generation and zonal load data. Natural gas prices and coal prices sold to fossil fuel power plants in ERCOT were collected from ABB. Table 3.1 presents summary statistics for the dependent and independent variables used in this work. Based on 201 different hourly nodal market prices, a discrete dependent variable was formalized that denotes hourly market condition as a class number.

3.3. Empirical Framework and Implementation Details

This paper implements two empirical methods. First, SOM neural networks were used to formalize a discrete dependent variable, for which hourly market outcomes (48,192 hours from 2011 to mid-2016) were transformed with 201 nodal market clearing prices into countable categories representing mutually exclusive ERCOT market conditions. Second, based on classified market conditions, a multinomial logistic regression model was run to investigate how interactions between CREZ projects and an increase of wind generation units in ERCOT contributed to shifts between classified market conditions.
3.3.1. Self-Organizing Map Neural Network (SOM)

*Unsupervised learning* refers to a machine learning algorithm used to draw inferences from datasets consisting of input data without labeled responses. The most common unsupervised learning method is a cluster analysis, which is used for explanatory data analysis to uncover hidden patterns or groupings in data. This paper uses SOM toolbox in MATLAB, which can learn the distribution and topology of input vectors. In this method, the user determines a number of neurons, the dimensions of a grid, and a grid structure for neuron connections. Generally, more neurons are needed to determine more complex data structures at higher computational costs. Typical SOM neurons range from a few dozen to a few hundred nodes. SOM employs a two-dimensional grid in most cases to replicate various data distributions. Figure 3.3 illustrates a two-dimensional grid of 100 neurons. The most common grid structures used in SOM is either a rectangular or a hexagonal grid, but there is no universal rule for choosing between two grid structures (Kohonen, 2014).\(^3\) The grid structure provides a way to connect neurons; a hexagonal arrangement for neurons indicates that each neuron is connected to six different neighboring neurons, whereas a rectangular grid shows that each neuron is connected to four neighboring neurons. The left panel in Figure 3.3 depicts a two-dimensional rectangular grid with 10 × 10 neurons, and the right indicates a hexagonal grid with 10 × 10 neurons.

With these initial settings, the SOM algorithm first randomly selects the initial neuron weights. All inputs are connected to each neuron; as such, the number of weights the SOM will find represents the number of input data dimensions multiplied by the number of neurons a user specifies. For example, the dataset in this study included 206 input dimensions representing 201 different nodes and five hourly summary statistics; I selected 16 neurons, leading to 3,296 weights. Second, the SOM algorithm selects one data point, either at random or systematically by cycling through the dataset in order. Third, the algorithm starts to minimize the distance from

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\(^3\) Note that there are many self-organizing models that do not consider a fixed grid topology, but a dynamic one, which is learned from the data distribution. The focus of the dynamic model, such as the Growing Neural Gas (GNG) and the Growing Cell Structures (GCS), is on learning a topology that reflects the structure of the data by adding new neurons and connections in a controlled manner.
neurons to data points, shifting neurons to data points. The distribution of neurons then begins to
replicate the shape of the data distribution, with the same type of data clustered in a center
neuron. Fourth, the second and third steps are repeated until the neuron positions become stable.
Finally, after $N$ iterations defined by the user, the results indicate the distance between neurons,
reflecting the similarity and discontinuity between neurons, and how many data points are
clustered in each center neuron.

Figure 3.4 presents toy examples of SOM estimation results. The left figure in panel (a) of Figure 3.4 shows the SOM estimation results with an artificial dataset for two-dimensional inputs with a two-dimensional hexagonal grid. After $N$ iterations, the neurons depicted as blue dots were clustered in the data points denoted as green dots and replicated the shape of the data distribution. Also, as in the right figure in panel (a), $8 \times 8$ neurons were trained for 20,000 iterations on a uniform double ring-distribution comprising artificial 10,000 data points. Panel (b) demonstrates how a two-dimensional rectangular grid can replicate three-dimensional data input: a $32 \times 32$ SOM was trained for 10,000 iterations on a set of 10,000 points uniformly distributed over diverse surfaces (Rougier and Boniface, 2011).

For the sake of simplicity, the classification result used in this paper is calculated by a $4 \times 4$ set of neurons (i.e., four neurons per dimension, equivalent to 16 neurons individually) and a hexagonal arrangement for the original neuron location (Figure 3.6). Section 3.4.1 addresses the selection process by comparing the main $4 \times 4$ result to the results with different settings, such as one-dimensional $1 \times 8$ grid structure, and two-dimensional $2 \times 4, 3 \times 3, 5 \times 5, 7 \times 7,$ and $10 \times 10$ grid structures. The dataset used for SOM implementation originally involved nodal market prices denoted as a $48,192 \times 201$ matrix, but the data were modified by subtracting hourly median values from 201 hourly nodal prices as this paper focuses mainly on price discrepancies throughout the ERCOT region. In other words, each column indicates how one hourly nodal price deviates from a median value of 201 hourly nodal prices. More columns were included to provide additional criteria for SOM clustering, such as the hourly mean, median, minimum,
maximum, and standard deviation of 201 nodal prices. Ultimately, the dimensions of the input
variables were 48,192 × 206.

3.3.2. Empirical Framework for CREZ Projects

After using SOM to classify the market conditions, a multinomial logistic regression was
estimated to investigate how CREZ projects and an increase in wind generation capacity
influenced the likelihood of each type of market condition as shown in the following equation:

\[
\text{Prob}(Y = j) = p_j = \frac{\exp(X\beta^j)}{\sum_{k=1}^{8} \exp(X\beta^k)}
\]

where \( X\beta^j = \beta_0^j + \beta_1^j CREZ_t + \beta_2^j Wind_t + \beta_3^j CREZ_t \times Wind_t + \gamma^j \Phi_t + \delta_{yh}^j + \epsilon_t \)

The probability of \( Y = j^{th} \) class depends on \( CREZ_t \) (the proportion of CREZ
completion); \( Wind_t \) (wind generation, denoted as GWh); and \( CREZ_t \times Wind_t \) (an interaction of
CREZ and wind generation). \( CREZ_t \) was set as 1 for 100% so the marginal effect with respect to
the covariate would reflect the impact of CREZ project completion on the probability of each
class. In addition, \( \Phi_t \) includes a set of covariates: zonal demand at four different load zones and
the ratio of natural gas prices to coal prices. Figure 3.1 shows the locations of load zones
throughout ERCOT. Although the current ERCOT market is divided into eight zones, data
analysis in this paper focused on four: North, Houston, West, and South. The North and Houston
zones account for approximately 37% and 27%, respectively, of energy sales in this market,
whereas the South and West zones contribute 12% and 9%. The North, Houston, South, and
West zones set the stage for nearly the entire state’s retail competition, and most competitive
generation occurs within these zones. The analysis did not include the Lower Colorado River
Authority, San Antonio, Austin, or Rayburn zones (also referred as LCRA, CPS, AEN, and
RAYBN, respectively) because each is dominated by a single vertically integrated utility system.
\( \Phi_t \) is the ratio of natural gas prices to coal prices sold to fossil fuel power plants in ERCOT.

Because natural gas power plants in ERCOT are normally marginal units, an increase in the ratio
encourages growth in market prices. Furthermore, the ratio can reflect the comparative advantage
between natural gas and coal power plants, both of which occupy more than 70% of electricity generation in ERCOT. Given that natural gas power plants are more dispatchable (i.e., they ramp up more quickly than coal units), an increase in the ratio could adversely affect market reliability and create more price spikes. Finally, \( \delta_{ydh} \) denotes year-day-hour fixed effects. Variables for the day fixed effect are dummies for weekends and holidays, and \( \epsilon_t \) is the error term.

3.4. Empirical Results

3.4.1. SOM Results

It is not possible to estimate or even guess the exact size of the neurons beforehand for an unknown data distribution. It must be determined by the trial-and-error method, after seeing the performance of the first guess (Kohonen, 2014). Accordingly, this paper conducts a variety of SOM estimations, starting from the simplest one (1 \( \times \) 8 grid structure), and selects a proper size that can reflect sufficiently heterogeneous market conditions that are related to the main purpose of this case study. In other words, with the set of covariates addressed in Section 3.3.2, we may not be able to derive causality of all detailed market conditions, especially reflecting (very) rare events.

Figure 3.5 presents a set of SOM results; SOM Neighbor Weight Distances denote topological distance between neurons and Hits show how many observations are clustered in each neuron. The color between neurons represents the distance: bright yellow indicates the two are close together, and dark red shows they are far apart. Based on the diverse settings, we can find a few consistent patterns of how SOM allocates a small number of neurons for a complex data structure. First, from panel (a) to (e), we can see that neurons are first allocated to some outliers and then, as we increase a size of neurons, more neurons are allocated to relatively common market conditions to further divide them. For example, until 3 \( \times \) 3, nine neurons, approximately 42,000 observations are clustered in one neuron, which may be a too coarse classification result for this study. Second, with the same logic, if one suspects that there are
interesting fine structures in the data and wants to investigate the details, then a larger set of neurons would be needed for sufficient resolution. For example, the hundred neurons (10 × 10) show that several neurons are allocated to the northeast region in the figure and the distances between neurons in the region are close each other. A further investigation demonstrates that those neurons simply classify the negative price conditions in west Texas into several different localized negative prices, such as negative prices in further west or negative prices in further north in west Texas. Finally, a multinomial logit regression used to investigate the interactive effects of CREZ projects and the wind generation on market conditions requires at least certain number of observations for each class. Even if the covariates used in the multinomial logit regression include diverse variables and time-fixed effects, we cannot technically derive causal inference for a rare market condition with only a few dozens of observations out of total 48,192 observations. In order to remedy the problem, the neurons having a few hundreds of observations should be either dropped out or combined to other neurons with similar characteristics. In this paper, I used a 4 × 4 set of neurons and combined two to three neurons having only a few hundreds of observations to one class.

Table 3.2 and Figures 3.6, 3.7, and 3.8 display the main SOM results. The names of each class were determined by considering the summary statistics in Table 3.2 along with the hourly means, minimums, and maximums for each class and, most importantly, a heat map of price dispersions in each class throughout ERCOT (Figure 3.8). Table 3.2 lists the names for Classes 1–8 (the row number corresponds to the class number) and indicates summary statistics for each class. During the time period for Class 1, defined as ‘(1) Base: Normal Condition,’ the average hourly minimum was $11.80, and the average hourly maximum was $31.40, a relatively stable condition given frequent and large fluctuations in nodal market prices in wholesale electricity markets. For example, Classes 3, 5, 7, and 8 represent either local or market-wide congestion and indicate that the average hourly maximum price was greater than $1,000. ‘(2) Negative Prices in W’ indicates the condition in which prices in west Texas are negative whereas those of other regions are stable and positive. ‘(3) Price Spikes in W’ represents localized price spikes (i.e.,
more than $500/MWh on average) in west Texas. ‘(4) High Prices in W’ denotes more moderate conditions than (3) but still higher prices in west Texas (approximately $100 on average) compared to other regions, which have normal ranges (approximately $30). ‘(5) Overall Price Spikes’ is defined for all nodal prices exhibiting excessively high prices (i.e., more than $500/MWh on average). (7) and (8) reflect localized price spike conditions for the South and Houston areas, respectively.

Because this study focuses on different market conditions with respect to price discrepancies over nodes, the SOM method with 16 neurons classified 96.9% of instances (approximately 46,700 observations) into three types: normal market conditions (78.6%), conditions for negative prices in west Texas (9.7%), and conditions for high prices in west Texas (8.6%). As discussed in Section 3.4.4, the normal market conditions were then further divided into four classes by another SOM estimation using Class 1. Every class identified by the subsequent SOM demonstrated moderate heterogeneity in terms of price discrepancies in ERCOT.

In Figure 3.6, each blue hexagon is a neuron, and the number in each hexagon denotes the number of observations clustered in that neuron, each of which may represent one class. Based on color between neurons, Classes 1 and 4 and Classes 4 and 2 were relatively close to each other; that is, normal market conditions (Class 1) were somewhat similar to localized high prices in west Texas (Class 4); however, Class 4 had lower prices in west Texas compared to those in Class 3, defined as market conditions involving price spikes in west Texas. SOM results also revealed that Class 4 appeared similar to Class 2, negative prices in west Texas. Price-spike classes (3, 5, and 7) were distant from others.

Figure 3.8 depicts the different price distributions for each class. Each heat map was drawn based on average hourly nodal prices. In Class 1, normal market conditions, all regions were green, suggesting that all average prices ranged from approximately $20–$70. The map for Class 2 clearly shows some negative nodal prices in west Texas, whereas Class 3 presents overall price spikes at nodes in west Texas. The map for Class 5 is also noteworthy, such that all average
nodal prices included price spikes, hence why all regions of Texas were red. Class 6 contained 465 observations (1% of all observations) and indicated heterogeneous nodal prices in all ERCOT areas but no recognizable patterns in terms of price discrepancies. In other words, SOM simply clustered all the other market conditions that were not classified in any of the other seven classes.

In terms of CREZ development, Figure 3.7 shows time trends in Classes 1–4. A blue line in each panel indicates the number of hours per month categorized as any of these four classes, respectively. The orange line in each panel indicates the CREZ construction progress in miles. For example, in a top panel graph, the hours for normal market conditions per month clearly increased during CREZ development. In addition, all other adverse market conditions that were likely to accompany increased wind generation were mitigated as CREZ development proceeded. The hours for negative prices in the west decreased substantially in 2013 and nearly disappeared after CREZ project completion in 2014. Also, CREZ development alleviated the hours characterized by high prices in west Texas (bottom panel). The figures also indicate seasonal time trends. For example, the market conditions of negative prices in the west were more likely when wind generation was relatively high and market demand was relatively low, as in the shoulder months. The second panel confirms this trend. Furthermore, high prices in west Texas appeared likely to occur more frequently when wind generation was relatively low but market demand was relatively high, such as during the summer (bottom panel).

3.4.2. Overall Results of Multinomial Logistic Regression

This section discusses how CREZ completion and an increase in wind generation affected the likelihood of a certain class. Columns 1 and 2 in Table 3.3 indicate the multinomial logistic regression results without an interaction term of CREZ and wind generation; Columns 3 and 4 show the results with the interaction term, which exhibited only slightly different magnitudes but the same directional impacts. Columns 3 and 4 are used for analysis in this paper.
In general, CREZ decreased adverse market conditions substantially. More specifically, occurrences of wind-related negative real-time electricity prices in west Texas declined by 15% as CREZ projects allowed wind power to flow to more areas with electricity demand in the state. Similarly, price spikes in west Texas declined by 2.6%, and high prices in the west fell by 8.5%. The reductions in the high price condition in west Texas reflect that CREZ projects also facilitated electricity imports from fossil fuel power plants outside west Texas when wind blew less in the west.

Increased wind generation, however, reduced the probability of normal conditions by 2.7% while increasing the chance of negative prices in west Texas by 5.4%, indicating that wind generation created surplus in west Texas. The results demonstrate a clear negative relationship between wind generation and the likelihood of market conditions reflecting price spikes in west Texas, which is also intuitive because high price conditions in west Texas were likely when wind generation drops. In the case of declining wind generation, lower-cost fossil fuel generators cannot ramp up quickly enough to compensate for lost wind generation; therefore, they must instead activate high-cost generators temporarily. Occasionally, it involves additional starting up of fossil fuel power plants.

Remarkably, price spikes in Houston were found to be 25% more likely after CREZ completion. As the market became increasingly integrated with CREZ, high prices in west Texas due to a temporary decline in wind generation attracted additional generation units that often supplied electricity exclusively to Houston prior to CREZ. In other words, even if low electricity prices from wind generation in west Texas reduced prices in other ERCOT regions after CREZ project completion, the adverse effects of intermittent wind generation spread to other regions.

Table 3.4 presents how other covariates affected market conditions, which can be summarized as follows. First, the connections between regional markets were not readily apparent. For example, localized price spikes in south and west Texas could occur due to increased regional demand as well as increased demand in other regions, such as north and south. Furthermore, even increased demand in other regions reduced the likelihood of price spikes in
south and west Texas. In a nodal market structure, the cost of an MWh and willingness to pay for it vary across the market footprint, and the manner in which the market has been cleared and connected can be difficult to discern. Thus, further investigation is needed to determine how best to infer hourly changing market connectivity in the electricity market via a nodal market structure. Second, an increase in the gas-to-coal price ratio can be expected to shift market conditions away from a normal market stage into a higher-price and price-spike stage.

3.4.3. Interactions

CREZ projects are primarily designed to move electricity generated from wind units from west Texas to more heavily populated areas as discussed in Section 3.2.2. Figure 3.9 illustrates how the average marginal impacts of CREZ change at different levels of wind generation (a CREZ value of 1 indicates 100%). The (1,1) panel shows that CREZ completion increased the probability of normal conditions under high levels of wind generation (i.e., greater than 10 GW), suggesting that ERCOT efficiently incorporated more wind generation with CREZ. When considering the (1,1) and (1,2) panels, CREZ appeared to shift the probability of negative prices in west Texas back to normal conditions especially when wind generation was high. In other words, CREZ contributed to wind generation exports from west Texas. Panels (2,1) and (2,2) indicate that CREZ remarkably decreased the probability of price spikes and high prices in west Texas at low levels of wind generation, implying that CREZ facilitated imports of electricity generated outside west Texas under low levels of wind generation. Finally, panel (4,2) shows that price spikes in Houston were more likely following CREZ completion when wind generation level was low.

Figure 3.10 presents average marginal impacts of wind generation on market conditions at different percentages of CREZ completion. All panels indicate that the adverse effects of wind generation disappeared after CREZ project completion even though the effects were quantitatively and statistically significant in the panels for both normal market and west Texas market conditions. Figure 3.11 indicates an interaction between CREZ and wind generation in a
more comprehensive perspective; blue regions reflect a negative marginal impact of wind generation, whereas red areas denote positive impacts and white regions indicate zero impact. The colored bars provide additional details. The grid points with dots represent statistically significant marginal impacts \((p < 0.05)\). As more CREZ projects were finished, impacts of intermittent wind generation were substantially mitigated. However, extreme wind generation values (whether low or high) nevertheless exerted adverse impacts on the market. For example, an increase in wind generation still resulted in some negative prices in west Texas even after CREZ completion at high levels of wind generation as in panel (1,2) in Figure 3.11. Panel (2,1) and (2,2) depict that when wind generation was low, a decline could also create high prices in the west even if the effects were greatly alleviated as more CREZ projects were undertaken. Essentially, even CREZ completion could not entirely mitigate the negative impacts of intermittent wind generation on market conditions when the generation was extreme.

### 3.4.4 Results with Different Settings

As outlined in Section 3.4.1, 78.6% of hours from 2011 to mid-2016 were classified as Class 1 (normal market conditions in terms of nodal price discrepancies) using the SOM method with 16 neurons. To ensure the robustness of the clustering results and the validity of the corresponding regression analysis, another SOM cluster was estimated using a partial dataset classified as Class 1.\(^4\) This subsequent SOM clustering procedure did not reveal any critical changes; Table 3.5 defines four classes and presents the regression results of all 11 classes. The four classes distinguished from Class 1 simply indicate parallel shifts in nodal market prices by a relatively small magnitude. For example, market conditions clustered in the ‘normal 2’ reflect a parallel upward shift of market-wide nodal prices in ‘normal 1.’ Regarding statistically significant marginal effects, the sum of the magnitudes of the four new classes is identical to the original magnitude. For instance, the cumulative impacts of wind generation on the four new classes was

\(^4\) Even though clustering with more neurons \((5 \times 5, 7 \times 7, \text{and } 10 \times 10)\) generated more classes, the results did not appear to create a new type of market condition in terms of market price discrepancies in ERCOT. However, further research will be conducted to investigate additional classes for market conditions using more detailed covariates.
found to be -2.78%, the same as the magnitude of wind on one class in the original model. All other magnitudes did not exhibit a statistically significant change, nor did the interaction effect (Figure 3.12). Table 3.6 and Figure 3.13 show another regression result with three main classes accounting for 96.9% of the observations. These results demonstrate that the marginal impacts of covariates had slightly different magnitudes but the same directional impacts, even with substantially different model specifications.

3.5. Conclusion

This paper analyzes the impacts of CREZ by considering its interaction with increased wind generation levels in ERCOT. To investigate the complex ERCOT market system, the study utilized a clustering method in machine learning to reduce the size of data dimensions while retaining valuable information. The clustering method classified diverse market conditions into eight categories. Overall, CREZ projects decreased nodal price discrepancies in ERCOT significantly. Occurrences of wind-related negative electricity prices in west Texas declined by 15%, and price spikes in west Texas fell by 11% as CREZ efficiently integrated supply and demand throughout ERCOT. However, market-wide analysis revealed that the integrated market was 25% more likely to cause price spikes in Houston as adverse impacts from intermittent wind generation in west Texas spread to other regions.

More importantly, as the installed wind capacity in ERCOT is expected to grow by another 63% from 2016–2020, this paper elucidates how wind generation has affected market conditions under different generation levels after CREZ completion. As expected, CREZ facilitated wind generation exports at high generation levels and imports at low generation levels. However, even when price discrepancies due to wind generation essentially disappeared following CREZ completion, extreme wind generation values (whether high or low) could still exacerbate ERCOT market conditions, which may worsen with other wind generation units in the region. From a policy perspective, other tools such as electricity storage facilities may be
considered to mitigate inefficient demand and supply clearing driven by increased intermittency with limited transmission capacities.

Future research should address a few additional factors. To more thoroughly quantify the economic benefits and costs of CREZ development and intermittent wind generation, the economic welfare of each type of market conditions should be estimated. Furthermore, an analysis of more segregated market classifications with additional covariates would offer valuable insights into the electricity wholesale market.
Table 3.1: Summary Statistics. This table summarizes the statistical distributions of both dependent and independent variables. Real time market prices are used for a clustering method.

<table>
<thead>
<tr>
<th>Variables</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real Time Market Price</td>
<td>9,686,592</td>
<td>29.74</td>
<td>22.73</td>
<td>-3618.11</td>
<td>6447.50</td>
</tr>
<tr>
<td>CREZ Construction (%)</td>
<td>48,192</td>
<td>0.62</td>
<td>0.38</td>
<td>0.11</td>
<td>1.00</td>
</tr>
<tr>
<td>Market Share of Wind (%)</td>
<td>48,192</td>
<td>11.36</td>
<td>8.11</td>
<td>0.02</td>
<td>48.16</td>
</tr>
<tr>
<td>Wind Generation (GWh)</td>
<td>48,192</td>
<td>4.03</td>
<td>2.59</td>
<td>0.01</td>
<td>13.89</td>
</tr>
<tr>
<td>Load Zone (AEN)</td>
<td>48,192</td>
<td>1.51</td>
<td>0.35</td>
<td>0.27</td>
<td>2.74</td>
</tr>
<tr>
<td>Load Zone (CPS)</td>
<td>48,192</td>
<td>2.61</td>
<td>0.73</td>
<td>0.43</td>
<td>4.99</td>
</tr>
<tr>
<td>Load Zone (Houston)</td>
<td>48,192</td>
<td>10.27</td>
<td>2.40</td>
<td>1.95</td>
<td>18.93</td>
</tr>
<tr>
<td>Load Zone (LCRA)</td>
<td>48,192</td>
<td>1.76</td>
<td>0.55</td>
<td>0.24</td>
<td>4.03</td>
</tr>
<tr>
<td>Load Zone (North)</td>
<td>48,192</td>
<td>14.03</td>
<td>3.75</td>
<td>2.13</td>
<td>27.90</td>
</tr>
<tr>
<td>Load Zone (RAYBN)</td>
<td>48,192</td>
<td>0.36</td>
<td>0.12</td>
<td>0.05</td>
<td>0.85</td>
</tr>
<tr>
<td>Load Zone (South)</td>
<td>48,192</td>
<td>4.53</td>
<td>1.13</td>
<td>0.88</td>
<td>8.51</td>
</tr>
<tr>
<td>Load Zone (West)</td>
<td>48,192</td>
<td>3.13</td>
<td>0.54</td>
<td>0.72</td>
<td>5.18</td>
</tr>
<tr>
<td>Natural Gas Price</td>
<td>48,192</td>
<td>3.28</td>
<td>0.91</td>
<td>1.40</td>
<td>8.58</td>
</tr>
<tr>
<td>Gas Price / Coal Price</td>
<td>48,192</td>
<td>1.69</td>
<td>0.47</td>
<td>0.73</td>
<td>4.29</td>
</tr>
</tbody>
</table>
Table 3.2: Clustering Result by Self Organizing Map Method. This table defines characteristics for class 1-8 (a row number corresponds to a class number) and indicates summary statistics for each class. Class 1 denoted as ‘Normal Condition’ represents the most stable market condition in terms of nodal price discrepancies over Texas electricity market. Class 2 indicates consistent negative prices in west Texas while class 4 denotes consistent high prices in west Texas. Class 1, 2, and 4 comprise 96.9% of observations. Class 3, 5, 7, and 8 representing either local or market-wide congestion indicate that an average of hourly maximum prices is greater than $1,000.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Base: Normal Condition</td>
<td>37,873 (78.6%)</td>
<td>-0.5</td>
<td>2.9</td>
<td>24.2</td>
<td>11.8</td>
<td>24.8</td>
<td>31.4</td>
</tr>
<tr>
<td>Negative Prices in W</td>
<td>4,662 (9.7%)</td>
<td>-4.4</td>
<td>13.1</td>
<td>16.4</td>
<td>-52.8</td>
<td>21.0</td>
<td>42.9</td>
</tr>
<tr>
<td>Price Spikes in W</td>
<td>302 (0.6%)</td>
<td>36.2</td>
<td>216.6</td>
<td>82.4</td>
<td>-69.4</td>
<td>39.3</td>
<td>1690.7</td>
</tr>
<tr>
<td>High Prices in W</td>
<td>4,145 (8.6%)</td>
<td>0.6</td>
<td>20.6</td>
<td>45.4</td>
<td>3.5</td>
<td>44.9</td>
<td>198.9</td>
</tr>
<tr>
<td>Overall Price Spikes</td>
<td>301 (0.6%)</td>
<td>-188.2</td>
<td>223.7</td>
<td>488.2</td>
<td>2.7</td>
<td>582.4</td>
<td>891.7</td>
</tr>
<tr>
<td>Hetero. Price (Random)</td>
<td>465 (1%)</td>
<td>11.6</td>
<td>93.1</td>
<td>64.7</td>
<td>-32.2</td>
<td>53.0</td>
<td>1018.0</td>
</tr>
<tr>
<td>Price Spikes in S</td>
<td>191 (0.4%)</td>
<td>33.4</td>
<td>262.6</td>
<td>106.6</td>
<td>-25.0</td>
<td>62.0</td>
<td>2545.5</td>
</tr>
<tr>
<td>Price Spikes in Houston</td>
<td>253 (0.5%)</td>
<td>9.1</td>
<td>95.8</td>
<td>40.9</td>
<td>10.46</td>
<td>31.5</td>
<td>1207.7</td>
</tr>
</tbody>
</table>
Table 3.3: Result of Multinomial Logit Regression (Key Variables). The columns (1) and (2) in this table indicate the multinomial logistic regression results without an interaction term of CREZ and wind generation and columns (3) and (4) show the results with the interaction term, which, as shown, have only slight different magnitudes but the same directional impacts. Columns (3) and (4) are used for the analysis in this paper. All standard errors are clustered by sample day and are reported in parentheses. ‘**’ represents the p-value is less than a certain threshold.

<table>
<thead>
<tr>
<th>CLASS</th>
<th>CREZ (%)</th>
<th>Wind Gen. (GWh)</th>
<th>CREZ (%)</th>
<th>Wind Gen. (GWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal Condition</td>
<td>0.0816</td>
<td>-0.0284***</td>
<td>0.0338</td>
<td>-0.0277***</td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td>(0.00193)</td>
<td>(0.135)</td>
<td>(0.00186)</td>
</tr>
<tr>
<td>Negative Prices in W</td>
<td>-0.209***</td>
<td>0.0532***</td>
<td>-0.153**</td>
<td>0.0541***</td>
</tr>
<tr>
<td></td>
<td>(0.0661)</td>
<td>(0.00124)</td>
<td>(0.0625)</td>
<td>(0.00113)</td>
</tr>
<tr>
<td>Price Spikes in W</td>
<td>-0.0260***</td>
<td>-0.00408***</td>
<td>-0.0260***</td>
<td>-0.00401***</td>
</tr>
<tr>
<td></td>
<td>(0.00633)</td>
<td>(0.000758)</td>
<td>(0.00635)</td>
<td>(0.000756)</td>
</tr>
<tr>
<td>Higher Prices in W</td>
<td>-0.0837***</td>
<td>-0.0175***</td>
<td>-0.0850***</td>
<td>-0.0189***</td>
</tr>
<tr>
<td></td>
<td>(0.0264)</td>
<td>(0.00125)</td>
<td>(0.0260)</td>
<td>(0.00122)</td>
</tr>
<tr>
<td>Overall Price Spikes</td>
<td>-0.00760</td>
<td>-0.00250***</td>
<td>-0.00763</td>
<td>-0.00240***</td>
</tr>
<tr>
<td></td>
<td>(0.00759)</td>
<td>(0.000418)</td>
<td>(0.00765)</td>
<td>(0.000431)</td>
</tr>
<tr>
<td>Hetero. Prices (Random)</td>
<td>-0.0138</td>
<td>-0.000149</td>
<td>-0.0138</td>
<td>-0.000117</td>
</tr>
<tr>
<td></td>
<td>(0.00961)</td>
<td>(0.000340)</td>
<td>(0.00960)</td>
<td>(0.000361)</td>
</tr>
<tr>
<td>Price Spikes in S</td>
<td>-0.00435</td>
<td>5.72e-05</td>
<td>-0.00429</td>
<td>0.000107</td>
</tr>
<tr>
<td></td>
<td>(0.00851)</td>
<td>(0.000191)</td>
<td>(0.00859)</td>
<td>(0.000209)</td>
</tr>
<tr>
<td>Price Spikes in Houston</td>
<td>0.262**</td>
<td>-0.000714*</td>
<td>0.256*</td>
<td>-0.00114**</td>
</tr>
<tr>
<td></td>
<td>(0.128)</td>
<td>(0.000371)</td>
<td>(0.133)</td>
<td>(0.000475)</td>
</tr>
<tr>
<td>CREZxWIND</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Year-Day-Hour FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>N</td>
<td>48,192</td>
<td>48,192</td>
<td>48,192</td>
<td>48,192</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1
Table 3.4: Result of Multinomial Logit Regression (All Variables). This table indicates how all the factors used in this paper affect classified market conditions. All standard errors are clustered by sample day and are reported in parentheses. ‘*’ represents the p-value is less than a certain threshold.

<table>
<thead>
<tr>
<th>CLASS</th>
<th>(1) CREZ (%)</th>
<th>(2) Wind Gen. (GWh)</th>
<th>(3) Load Zone (Houston)</th>
<th>(4) Load Zone (North)</th>
<th>(5) Load Zone (South)</th>
<th>(6) Load Zone (West)</th>
<th>(7) Gas/Coal Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal Condition</td>
<td>0.0338</td>
<td>-0.0277***</td>
<td>-0.00263</td>
<td>0.00842***</td>
<td>-0.0336**</td>
<td>-0.0635**</td>
<td>-0.0332**</td>
</tr>
<tr>
<td></td>
<td>(0.135)</td>
<td>(0.00186)</td>
<td>(0.00565)</td>
<td>(0.00373)</td>
<td>(0.0134)</td>
<td>(0.0283)</td>
<td>(0.0149)</td>
</tr>
<tr>
<td>Negative Prices in W</td>
<td>-0.153**</td>
<td>0.0541***</td>
<td>-0.00122</td>
<td>-0.00520*</td>
<td>0.0162*</td>
<td>-0.0405**</td>
<td>-0.0180*</td>
</tr>
<tr>
<td></td>
<td>(0.0625)</td>
<td>(0.00113)</td>
<td>(0.00431)</td>
<td>(0.00273)</td>
<td>(0.00930)</td>
<td>(0.0204)</td>
<td>(0.00943)</td>
</tr>
<tr>
<td>Price Spikes in W</td>
<td>-0.0260***</td>
<td>-0.00401***</td>
<td>-0.000980</td>
<td>-0.00273***</td>
<td>0.00441*</td>
<td>0.0198***</td>
<td>0.00518*</td>
</tr>
<tr>
<td></td>
<td>(0.00635)</td>
<td>(0.000756)</td>
<td>(0.000847)</td>
<td>(0.000717)</td>
<td>(0.00252)</td>
<td>(0.00633)</td>
<td>(0.00266)</td>
</tr>
<tr>
<td>Higher Prices in W</td>
<td>-0.0850***</td>
<td>-0.0189***</td>
<td>0.00972***</td>
<td>-0.00339</td>
<td>-0.00231</td>
<td>0.0995***</td>
<td>0.0586***</td>
</tr>
<tr>
<td></td>
<td>(0.0260)</td>
<td>(0.00122)</td>
<td>(0.00321)</td>
<td>(0.00210)</td>
<td>(0.00836)</td>
<td>(0.0161)</td>
<td>(0.00913)</td>
</tr>
<tr>
<td>Overall Price Spikes</td>
<td>-0.00763</td>
<td>-0.00240***</td>
<td>-0.000704</td>
<td>0.00235***</td>
<td>-0.00127</td>
<td>-0.00505</td>
<td>0.00267*</td>
</tr>
<tr>
<td></td>
<td>(0.00765)</td>
<td>(0.000431)</td>
<td>(0.000694)</td>
<td>(0.000704)</td>
<td>(0.00155)</td>
<td>(0.00440)</td>
<td>(0.00145)</td>
</tr>
<tr>
<td>Hetero. Prices (Random)</td>
<td>-0.0138</td>
<td>-0.000117</td>
<td>-0.00350***</td>
<td>0.000215</td>
<td>0.00889***</td>
<td>0.00805*</td>
<td>0.00235</td>
</tr>
<tr>
<td></td>
<td>(0.00960)</td>
<td>(0.000361)</td>
<td>(0.000880)</td>
<td>(0.000858)</td>
<td>(0.00210)</td>
<td>(0.00464)</td>
<td>(0.00322)</td>
</tr>
<tr>
<td>Price Spikes in S</td>
<td>-0.00429</td>
<td>0.000107</td>
<td>-0.00226***</td>
<td>0.00123**</td>
<td>0.00634***</td>
<td>-0.0102***</td>
<td>-0.00221</td>
</tr>
<tr>
<td></td>
<td>(0.00859)</td>
<td>(0.000209)</td>
<td>(0.000725)</td>
<td>(0.000534)</td>
<td>(0.00140)</td>
<td>(0.00304)</td>
<td>(0.00254)</td>
</tr>
<tr>
<td>Price Spikes in Houston</td>
<td>0.256*</td>
<td>-0.00114**</td>
<td>0.00157</td>
<td>-0.000889</td>
<td>0.00138</td>
<td>-0.00806</td>
<td>-0.0153**</td>
</tr>
<tr>
<td></td>
<td>(0.133)</td>
<td>(0.000475)</td>
<td>(0.00154)</td>
<td>(0.000869)</td>
<td>(0.00364)</td>
<td>(0.00669)</td>
<td>(0.00611)</td>
</tr>
<tr>
<td>CREZxWIND</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Year-Day-Hour FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
</tbody>
</table>

Observations 48,192 48,192 48,192 48,192 48,192 48,192 48,192

*** p<0.01, ** p<0.05, * p<0.1
Table 3.5: Result of Multinomial Logit Regression with More Classes. This table indicates a regression result with four classes segmented from class 1 having 78.6% of observations. This result with 11 classes does not generate any critical change. All standard errors are clustered by sample day and are reported in parentheses. ‘*’ represents the p-value is less than a certain threshold.

<table>
<thead>
<tr>
<th>CLASS</th>
<th>CREZ (%)</th>
<th>Wind Gen. (GWh)</th>
<th>Load Zone (Houston)</th>
<th>Load Zone (North)</th>
<th>Load Zone (South)</th>
<th>Load Zone (West)</th>
<th>Gas/Coal Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal 1 (Normal)</td>
<td>0.0288</td>
<td>-0.00830***</td>
<td>-0.00586</td>
<td>-0.00939**</td>
<td>-0.0684***</td>
<td>0.0150</td>
<td>-0.278***</td>
</tr>
<tr>
<td></td>
<td>(0.0883)</td>
<td>(0.00179)</td>
<td>(0.00665)</td>
<td>(0.00445)</td>
<td>(0.0139)</td>
<td>(0.0319)</td>
<td>(0.0178)</td>
</tr>
<tr>
<td>Normal 2 (Overall Inc.)</td>
<td>0.0811</td>
<td>-0.0111***</td>
<td>-0.00899*</td>
<td>0.0141***</td>
<td>0.0384***</td>
<td>-0.106***</td>
<td>0.158***</td>
</tr>
<tr>
<td></td>
<td>(0.0562)</td>
<td>(0.00164)</td>
<td>(0.00502)</td>
<td>(0.00346)</td>
<td>(0.0104)</td>
<td>(0.0250)</td>
<td>(0.0141)</td>
</tr>
<tr>
<td>Normal 3</td>
<td>0.00875</td>
<td>-0.00134***</td>
<td>0.00703***</td>
<td>-0.00457***</td>
<td>0.00457</td>
<td>0.0259***</td>
<td>-0.00493</td>
</tr>
<tr>
<td></td>
<td>(0.0134)</td>
<td>(0.000581)</td>
<td>(0.00177)</td>
<td>(0.00135)</td>
<td>(0.00423)</td>
<td>(0.00969)</td>
<td>(0.00591)</td>
</tr>
<tr>
<td>Normal 4</td>
<td>-0.0259</td>
<td>-0.00706***</td>
<td>0.00320*</td>
<td>0.00638***</td>
<td>-0.000220</td>
<td>-0.0159</td>
<td>0.0675***</td>
</tr>
<tr>
<td></td>
<td>(0.0219)</td>
<td>(0.000712)</td>
<td>(0.00179)</td>
<td>(0.00131)</td>
<td>(0.00425)</td>
<td>(0.00998)</td>
<td>(0.00611)</td>
</tr>
<tr>
<td>Negative Prices in W</td>
<td>-0.179**</td>
<td>0.0538***</td>
<td>0.00165</td>
<td>-0.00562*</td>
<td>0.0117</td>
<td>-0.0246</td>
<td>-0.0167*</td>
</tr>
<tr>
<td></td>
<td>(0.0740)</td>
<td>(0.00118)</td>
<td>(0.00490)</td>
<td>(0.00294)</td>
<td>(0.0104)</td>
<td>(0.0223)</td>
<td>(0.00987)</td>
</tr>
<tr>
<td>Price Spikes in W</td>
<td>-0.0268***</td>
<td>-0.00392***</td>
<td>-0.000985</td>
<td>-0.00252***</td>
<td>0.00435*</td>
<td>0.0192***</td>
<td>0.00574*</td>
</tr>
<tr>
<td></td>
<td>(0.00662)</td>
<td>(0.000751)</td>
<td>(0.000882)</td>
<td>(0.000703)</td>
<td>(0.00259)</td>
<td>(0.00623)</td>
<td>(0.00313)</td>
</tr>
<tr>
<td>Higher Prices in W</td>
<td>-0.0987***</td>
<td>-0.0185***</td>
<td>0.00909***</td>
<td>-0.00155</td>
<td>-0.00579</td>
<td>0.100***</td>
<td>0.0754***</td>
</tr>
<tr>
<td></td>
<td>(0.0260)</td>
<td>(0.00126)</td>
<td>(0.00342)</td>
<td>(0.00211)</td>
<td>(0.00905)</td>
<td>(0.0165)</td>
<td>(0.0111)</td>
</tr>
<tr>
<td>Overall Price Spikes</td>
<td>-0.0106</td>
<td>-0.00251***</td>
<td>-0.000582</td>
<td>0.00225***</td>
<td>-0.00166</td>
<td>-0.00335</td>
<td>0.00347***</td>
</tr>
<tr>
<td></td>
<td>(0.00858)</td>
<td>(0.000442)</td>
<td>(0.000679)</td>
<td>(0.000666)</td>
<td>(0.00158)</td>
<td>(0.00431)</td>
<td>(0.00170)</td>
</tr>
<tr>
<td>Hetero. Prices (Random)</td>
<td>-0.0149</td>
<td>-8.12e-05</td>
<td>-0.00371***</td>
<td>0.000401</td>
<td>0.00904***</td>
<td>0.00724</td>
<td>0.00599</td>
</tr>
<tr>
<td></td>
<td>(0.00959)</td>
<td>(0.000363)</td>
<td>(0.000885)</td>
<td>(0.000855)</td>
<td>(0.00220)</td>
<td>(0.00467)</td>
<td>(0.00521)</td>
</tr>
<tr>
<td>Price Spikes in S</td>
<td>-0.00379</td>
<td>0.000147</td>
<td>-0.00244***</td>
<td>0.00136***</td>
<td>0.00652***</td>
<td>-0.0109***</td>
<td>-0.000658</td>
</tr>
<tr>
<td></td>
<td>(0.00822)</td>
<td>(0.000208)</td>
<td>(0.000808)</td>
<td>(0.000574)</td>
<td>(0.00162)</td>
<td>(0.00335)</td>
<td>(0.00320)</td>
</tr>
<tr>
<td>Price Spikes in Houston</td>
<td>0.241*</td>
<td>-0.00105**</td>
<td>0.00160</td>
<td>-0.000815</td>
<td>0.00145</td>
<td>-0.00714</td>
<td>-0.0154**</td>
</tr>
<tr>
<td></td>
<td>(0.129)</td>
<td>(0.000466)</td>
<td>(0.00154)</td>
<td>(0.000888)</td>
<td>(0.00367)</td>
<td>(0.00656)</td>
<td>(0.00610)</td>
</tr>
<tr>
<td>CREZxWIND Year-Day-Hour FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Observations</td>
<td>48,192</td>
<td>48,192</td>
<td>48,192</td>
<td>48,192</td>
<td>48,192</td>
<td>48,192</td>
<td>48,192</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1
Table 3.6: Result of Multinomial Logit Regression with Three Main Classes. This table shows a regression result only with three main classes occupying 96.9% of observations. All standard errors are clustered by sample day and are reported in parentheses. ‘**’ represents the p-value is less than a certain threshold.

<table>
<thead>
<tr>
<th>CLASS</th>
<th>(1)</th>
<th>(2)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal Condition</td>
<td>0.231*** (0.0675)</td>
<td>-0.0335*** (0.00174)</td>
<td>-0.00624 (0.00542)</td>
<td>0.00764** (0.00350)</td>
<td>-0.0183 (0.0127)</td>
<td>-0.0628** (0.0267)</td>
<td>-0.0452*** (0.0134)</td>
</tr>
<tr>
<td>Negative Prices in W</td>
<td>-0.155** (0.0641)</td>
<td>0.0557*** (0.00115)</td>
<td>-0.00271 (0.00442)</td>
<td>-0.00412 (0.00277)</td>
<td>0.0175* (0.00960)</td>
<td>-0.0451** (0.0212)</td>
<td>-0.0183* (0.00968)</td>
</tr>
<tr>
<td>Higher Prices in W</td>
<td>-0.0754*** (0.0240)</td>
<td>-0.0223*** (0.00127)</td>
<td>0.00895*** (0.00263)</td>
<td>-0.00353 (0.00218)</td>
<td>0.000818 (0.00383)</td>
<td>0.108*** (0.0167)</td>
<td>0.0634*** (0.00939)</td>
</tr>
<tr>
<td>CREZxWIND Year-Day-Hour FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1
Figure 3.1: Load Zones in Texas Wholesale Electricity Market. Points on the map indicate approximate locations of transmission nodes.
Figure 3.2: CREZ Transmission Projects Locations.
**Figure 3.3**: 2-Dimensional SOM Grid Examples. The left panel shows a 2-dimensional rectangular grid with 10-by-10 neurons and the right one indicates hexagonal grid with 10-by-10 neurons.
Figure 3.4: SOM Estimation Examples. These figures show the SOM estimation examples with a 2-dimensional grid. Panel (a) indicates the estimation results for 2-dimensional input data. The green dots in the left panel represent data points and blues dots show locations of neurons after the SOM estimation. The blue dots in the right panel show data points and white dots denote locations of neurons after the estimation. Panel (b) shows the results for 3-dimensional input data, which demonstrate that a 2-dimensional grid can replicate any shapes of data distribution, such as a sphere surface, a cube surface and a more complex shape.
Figure 3.5: Clustering Results with SOM Method with different settings.
Figure 3.6: Clustering Results with SOM Method. Each blue hexagon indicates a neuron and a number in each hexagon shows the number of observations clustered for the neuron, each of which may denote one class. The color between neurons represents the distance; Bright yellow indicates that the two are close together while dark red shows that the two are far apart. Based on the figure, we can infer that class 1 and 4 and class 4 and 2 are relatively close each other. In other words, normal market conditions numbered as class 1 are somewhat similar to the conditions of localized high prices in west Texas, numbered as 4 (however, the class 4 has lower prices in west Texas than the ones in class 3 defined for market conditions for price spikes in west Texas). Furthermore, by the SOM method, the class 4, high prices in west Texas’, is also considered similar to class 2 that is defined as ‘negative prices in west Texas’. In addition, we can see that classes for price spikes (3,5, and 7) are distant from other classes.
Figure 3.7: Time Trend of Class 1 to 4. These figures show time trends in occurrences of the class 1 to 4. A blue line in each panel shows how many hours per month are classified as class 1 to 4, respectively. An orange line in each panel indicates the CREZ construction progress in miles. For example, as in a top panel graph, the hours for normal market conditions per month have clearly increased in the CREZ development.
**Figure 3.8**: Price Dispersion Map for Classes. Following figures show contour surface maps of nodal prices ($) for 8 classes clustered by Self Organizing Map. Each nodal price in a class map is averaged over a time period (observations) for each class. A color bar in figure indicates the color scale.
Figure 3.9: Impacts of CREZ on Market Conditions at Different Levels of Wind Generation. A set of figures indicates how the CREZ affects a marginal probability of being each class at different levels of wind generation. Blue lines indicate average impacts of CREZ on classes and error bars show 95% confidence intervals. Positive values in a class denote that CREZ completion has increased the probability of a market condition being classified as the class. In summary, CREZ completion increases the probability of normal condition while decreasing all other probabilities on adverse market conditions except class 8. Class 1 to 4 show remarkable interactions. Also, it is worth noting that the bottom right panel indicates the CREZ development can increase the probability of price spikes in Houston by 25% on average. Section 3.4.2. addresses all the details.
Figure 3.10: Impacts of Wind Generation on Market Conditions at Different Levels of CREZ Development. A set of figures indicates how wind generation affects a marginal probability of being each class with different levels of CREZ completion on average. Blue lines indicate impacts of Wind generation and error bars show 95% confidence intervals. Positive values in each class denote that a wind generation increase has increased the probability of a market condition being classified as the class. Wind generation changes have significant impacts on class 1-4, while the percent of CREZ completion is approximately less than 60%. In other words, after the CREZ completion, the adverse effects caused by wind generation have almost disappeared.
Figure 3.11: Impacts of Wind Generation on Market Conditions at Different Levels of both CREZ Development and Wind Generation. A set of figures shows how a marginal wind generation increase (1 GW) at a different level of wind generation can change the probability of being each class with a different percentage of CREZ completion. Blue regions reflect the marginal impact of wind generation is negative while red areas denote positive impacts. White regions simply reflect zero impacts. The grid points with dots represents the marginal impacts on the dots are statistically significant (p-values is less than 0.05).
Figure 3.12: Interactions between Wind Generation and CREZ on Additional Classes. This set of figures show interactions of wind generation and CREZ on four classes originally classified as class 1.
Figure 3.13: Interactions between Wind Generation and CREZ on Class 1, 2, and 4. This set of figures shows multinomial logistic regression results estimated by three types of market conditions, which in total cover 96.9% of observations in data. Blue lines indicate average impacts and error bars show 95% confidence intervals. Left three panels show average impacts of CREZ on the different types of market conditions. Right three panels show average impacts of wind generation on the different types of market conditions.
REFERENCES


Affect Efficiency? Evidence from Electricity Markets.”


Appendix A

Additional Solutions of the Theoretical Model for Chapter 1

Equation 1 shows the clearing prices and cleared quantities at equilibrium in the baseline model (section 2.1).

\[ q^*_A = \frac{2Ab_{RT} - Ab_{DA} - b_{DA}b_{RT}C}{4b_{RT} - b_{DA}} \]  
\[ p^*_A = \frac{2Ab_{RT} + b_{DA}b_{RT}C}{b_{DA}(4b_{RT} - b_{DA})} \]  
\[ q^*_R = \frac{b_{RT}(A + (b_{DA} - 2b_{RT})C)}{4b_{RT} - b_{DA}} \]  
\[ p^*_R = \frac{A + 2b_{RT}C}{4b_{RT} - b_{DA}} \]

Equation 2 shows the clearing prices and cleared quantities at equilibrium in the model with wind generation (section 2.2).

\[ q^*_A = \frac{b_{DA}(w_{DA} + w_{RT} - A) + 2b_{RT}(A - w_{DA}) - b_{DA}b_{RT}C}{4b_{RT} - b_{DA}} \]  
\[ p^*_A = \frac{2Ab_{RT} - 2b_{RT}w_{DA} + b_{DA}(b_{RT}C - w_{RT})}{b_{DA}(4b_{RT} - b_{DA})} \]  
\[ q^*_R = \frac{b_{RT}(A + (b_{DA} - 2b_{RT})C - w_{DA} - 2w_{RT})}{4b_{RT} - b_{DA}} \]  
\[ p^*_R = \frac{A + 2b_{RT}C - w_{DA} - 2w_{RT}}{4b_{RT} - b_{DA}} \]
Appendix B

Institutional Background for Chapter 1

B1. Nodal Market

The ERCOT market uses a network operation model, which represents the complete transmission grid as a set of more than 4,000 network nodes (Figure D4). These 4,000 points of interconnection with the system may be an energy source (injection point), sink (withdrawal point), or switching station (transformation point). Among the 4,000 nodes, there are three types of settlement points in the nodal market: resource nodes, load zones, and hubs. A resource node represents a point where generation output and Locational Marginal Pricing (LMP) are measured. Out of 676 resource nodes, 469 are connected to fossil-fueled generators.

The LMP establishes a price per MWh at a given network node based on the marginal cost of delivering the next MW to that node. LMP will be the same throughout the system if there is no congestion. If congestion does exist, however, LMP will differ from node to node. The distinction between zonal and local congestion disappears as all congestion is managed using individual resources instead of portfolios. In other words, LMPs can be the same, higher, or lower than a specific offer price at a given node (ERCOT, 2010). Different LMPs provide a signal that something reliability-related is limiting the network. In figure D5, the left panel shows an example of a network under normal conditions, meaning no congestion or outages. In this case, generator 2 has the lowest offer and will serve the entire load, and the cheaper LMP of $2 applies to all the nodes. A sum of $20 is paid to the generator and charged to loads. However, the right panel of figure D5 shows a case with congestion, which may be caused by an outage, transmission constraint, or unexpected high demand. This example explains a transmission

---

1 Substations transform voltage from high to low, or the reverse, or perform any of several other important functions. Between the generating station and the consumer, electric power may flow through several substations at different voltage levels. A substation may include transformers to change voltage levels between high transmission voltages and lower distribution voltages, or at the interconnection of two different transmission voltages.
constraint. The lowest priced generator B cannot serve the entire load, and generator A must serve 6 MW. So, generator A will supply 6 MW at $4/MWh while generator B will serve 4 MW at $2/MWh. The two LMPs are different accordingly.

In Day-Ahead Market (DAM), Settlement Point Prices (SPP) represent just LMP at the resource nodes. In Real-Time Market (RTM), however, SPP are calculated as the sum of LMP and reserve price adders. In this paper, SPP in DAM and RTM are employed to analyze the market. Figure D6 shows the ERCOT-wide SPP in DAM and RTM for 2-3 PM on a certain day. Prices were heterogeneous throughout nodes in both DAM and RTM, and nodal prices in RTM ranged between -$112.45 and $830.73, caused by congested nodes in the system.

B2. Dynamic Constraint and Market Demand

The electricity generation industry, in general, has unusual characteristics. First, the generators have capacity constraints. The maximum output capacity is set at the time of construction and usually does not change. Generators also have an implicit minimum output capacity to sustain their operations without shutting down. Operating below the minimum output level results in large inefficiencies and may damage generating equipment. Second, electric power plants have significant costs when starting up (market entry) and shutting down (market exit) generators. The startup costs are unavoidable fixed costs but are recursively required whenever a generator is brought to the market after a period of zero production. The startup costs are needed to heat up equipment, bring turbines up to a proper speed, and employ additional laborers to supervise the process. According to engineering research, the startup and shut down also require additional maintenance costs in the long run. Engineering estimates of startup costs range from hundreds of dollars to hundreds of thousands of dollars per start, and the cost depends on the size and technology of the generators. The technologies of each type of generator differ with respect to

ERCOT has two types of reserve prices as incentives to ensure that sufficient energy generation resources will be online: 1) ancillary service prices and quantities competitively procured by bids from firms in DAM and 2) reserve price adders calculated based on the Operating Reserve Demand Curve (ORDC). ERCOT implemented an ORDC to reflect the inverse relationship between the reserve price adder and the currently available system-wide reserve on June 1, 2014, which precisely represents an actual price change for the Ancillary Service Imbalance.
operational aspects and economics. It is, for example, more costly and time-consuming to start up nuclear and coal power stations than natural gas power plants. These capacity constraints and startup costs limit the ability of firms to change production over time, exacerbating fluctuations in market prices (Reguant, 2014).

Third, the demand for electricity is almost perfectly inelastic to price change in the short-run because only a few customers are able to adjust their consumption in response to changing market conditions. The usual consumers are likely to react to the change in the average price of electricity rather than the instant marginal price change because only monthly utility bills are normally salient to consumers (Ito, 2014). However, the quantity of electricity demanded at a given price varies cyclically throughout the day and the year. Peak demand can be twice as high as off-peak demand within the same day. Thus, the wholesale market price of electricity varies over time to cope with the fluctuating demand. Finally, because the electricity cannot be stored in meaningful amounts, electricity generation and consumption must be balanced at every second to prevent a brownout (dropping electrical frequency) or blackout (complete loss of electric service). This reliability issue is important in the power sector because it creates a large social cost.

**B3. Bids in the Day-Ahead and Real-Time Markets**

Bids to offer can take the form of either a three-part supply offer (TP), which allows sellers to reflect the unique financial and operational characteristics of a specific generation resource (startup offer, minimum energy offer, and energy offer curve), or an energy-only offer (offers for the virtual market only with offer curves), which is location-specific but is not associated with a generation resource. Bids to buy are also location-specific and not associated with a generation resource. While three-part supply offers are submitted by only QSEs that own energy resources,

---

3 Even if some states tried to employ smart metering and dynamic pricing models so that residential consumers could counteract price volatility, there exist controversial debates on the actual efficacy of the device, as many researchers argue (Ito, 2014). Thus, even in states utilizing a deregulated or restructured electricity wholesale market, the electricity retail market is actually regulated by a fixed price.
the energy-only offers can be submitted by any QSEs. If a QSE with resources chooses to submit an energy offer curve without a startup offer and a minimum energy offer, the QSE would be considered as stating a willingness to offer the energy from the unit without consideration of the cost of starting the unit. The energy-only offers are mainly (but not necessarily) submitted by QSEs without resources who are financial speculators in the market.
Appendix C

Machine Learning Method (Dynamic Neural Networks) for Chapter 1

Neural networks can be classified into dynamic and static categories. Static networks have no feedback elements (lagged outputs) and contain no delays (lagged inputs). In other words, the output is calculated directly from the input through feedforward connections. In dynamic networks, however, the output depends not only on the current input to the network but also on the current or previous inputs, outputs, or states of the network. Dynamic networks are generally more powerful than static networks, although they are somewhat more difficult to train (Beale et al, 2018).

Because dynamic networks have memory, they can be trained to learn sequential or time-varying patterns. This method can be applied to prediction in financial markets, channel equalization in communication systems, phase detection in power systems, sorting, speech recognition, and even the prediction of protein structure in genetics.

C1. Structure of DNN

I begin by describing the simplest possible neural network, one that comprises a single neuron. The single neuron is a computational unit that takes as input vector \( P \) whose length is the number of covariates (\( R \)). Then, the output of a neuron (\( a \)) is:

\[
a_{W,b} (P) = f(W^T P) = f\left(\sum_{i=1}^{R} w_i p_i + b \right)
\]

, where \( w_i \) is weight for \( i^{th} \) input, \( b \) denotes a value for bias (intercept), and \( f \) is a differentiable transfer function.

As a neural network normally has multiple neurons, however, Figure D7-1 shows an architecture of a one-layer network with \( R \) input elements and \( S \) neurons. Neurons can use any differentiable transfer function \( f \) to generate their output.
Also, to solve more complex problems in the real world, such as image recognition, operating a self-driving car, playing Go, and so on, we need multiple layers with multiple neurons (Figure D7-2) and brilliant transfer functions; these are called deep neural nets. In figure D7-2, the leftmost layer of the network is called the input layer, and the rightmost layer the output layer. The middle layer of nodes is called the hidden layer because its values are not observed in the training set.

In this paper, I used 3 layers composed of one input layer, a hidden layer, and an output layer with two transfer functions between layers, which are a form of non-linear transformation from hidden to output layer and simple linear transformation from the output layer to the final predictions (Figure D7-3). This network design is a standard in neural networks to implement a general function approximation method and can approximate any function with a finite number of discontinuities arbitrarily well, given a sufficient number of neurons in the hidden layer.

While the number of neurons in the input layer is the same as the number of covariates, and the number for the output layer is just the number of outputs, a user needs to define a number of neurons in a hidden layer based on the size of inputs and outputs, the complexity of a problem, and possible overfitting problems. I used 75-200 neurons in the hidden layer, taking into account a large number of input variables in my data sets, as well as heterogeneous targets (dependent variables).

After setting up a number of neurons and layers, the final choice of parameters and model selection for optimal prediction functions is the one that minimizes the mean of the squared errors (MSE) for the difference between actual targets $Y_i$ and predicted targets $\hat{Y}_i$:

$$
MSE = \frac{1}{N} \sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2
$$

In addition, the machine learning method is equipped with a myriad of effective tools in order to find a sweet spot between balancing bias (overfittings) and variance (mean-squared errors) of prediction results, which are addressed in the following section.

---

4 I used a tangent sigmoid transfer function: $\text{tanh}(x) = \frac{1-e^{-2x}}{1+e^{-2x}}$
C2. Complementary Tools

I employed random sample splitting and early stopping methods to prevent potential overfittings. With the two methods, the data set is randomly split into a training sample and a validation sample. In this paper, the validation sample has 30 percent of randomly selected observations. The remainder of the training sample is used for estimation. The estimation results are then used to predict outcomes for the left-out validation sample at every iteration. As soon as MSE for predicted outcomes based on the validation sample starts increasing, the training process stops and a prediction function is determined by a set of tuning parameters for covariates at the iteration. This early stopping may be able to prevent the overfitting of prediction models and put more emphasis on finding predictive power over out of sample.

With this process, however, the tuned parameters for a prediction model can be different at each trial because it depends on the random sample splitting and an initial guess for parameter values for prediction models in the stochastic gradient descent (SGD) routine. Thus, in general, the random sample splitting with the early stopping process has been done several times. In this paper, I iterated the process 50 times and generated predictions by averaging out those 50 individual prediction results. In fact, an important insight from machine learning is that averaging over many small models tends to provide better out-of-sample predictions than does choosing a single model (Varian, 2014).

C3. Prediction Accuracy Assessment

Ultimate model performance is assessed by calculating the mean-squared error of model predictions (that is, the sum of squared residuals) on the held-out test sample, which was not used at all for model estimation or tuning. This assessment can be used to select the best

---

5 There are other tools that can attenuate overfittings of the models. For example, the Bayesian regularization method is a powerful tool to prevent overfitting when solving very complex problems with relatively small data sets. It does not necessarily need the other tools (such as cross-validation) to prevent overfitting. However, it is computationally expensive.

6 Stochastic gradient descent is a stochastic approximation of the gradient descent optimization method for minimizing objective function. In other words, it finds minima and maxima by step-wise iterations.
prediction model among candidates (50 prediction models in this paper). Instead, I use the
assessment just for reference and yet, employ all 50 prediction models by taking the average, 
with a randomly split validation set for training, to find robust network performances in the 
overall data set. I choose this approach mainly because first, the data in ERCOT are quite 
heterogeneous over time. Second, trainings with random sample splitting can be sufficient to 
generalize the prediction models and prevent potential overfittings. Finally, predictions of good 
quality can generally be obtained by combining a small number of carefully chosen models. For 
some difficult problems, this random sample splitting and averaging process can improve 
performances and generalize the prediction models well.

Also, it is important to note that predictions from these machine learning methods are not 
typically unbiased, and estimators may not be asymptotically normal and centered around the 
estimand. Indeed, the machine learning literature places little emphasis on asymptotic normality, 
and when theoretical properties are analyzed, they often take the forms of worst-case bounds on 
loss functions. However, the fact that model performance (in the sense of predictive accuracy on 
a test set) can be directly measured makes it possible to compare predictive models even when 
their asymptotic properties are not understood (Athey and Imbens, 2017).

---

7 For example, wind capacity has been consistently increased since 2011 and will increase for the next 5 years (See 
figure 2).
Appendix D

Additional Tables and Figures for Chapter 1

Table D1: Decomposition of Ancillary Service Cost Changes with a 20% Wind Increase. This table shows how generation from renewable energy pushes down energy prices. The overall decrease in electricity market prices driven by a wind generation increase at zero marginal cost has significantly decreased ancillary service prices. So, even if the reserve operations increase with wind penetration, the decrease in reserve market price outweighs the impact and thus leads to a decrease in total reserve costs, which contradicts the predictions of engineering studies.

<table>
<thead>
<tr>
<th>Volatility</th>
<th>Forecast Errors</th>
<th>Wind Only</th>
<th>ALL</th>
</tr>
</thead>
<tbody>
<tr>
<td>AS Prices</td>
<td>$0.12</td>
<td>$0.64</td>
<td>-$1.45</td>
</tr>
<tr>
<td>AS Quantities</td>
<td>$693,058</td>
<td>$3,333,087</td>
<td>-$6,520,728</td>
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**Figure D1: Installed and Projected Wind Generation Capacities in ERCOT**

<table>
<thead>
<tr>
<th>Year</th>
<th>Cumulative MW Installed</th>
<th>IA Signed-Financial Security Posted</th>
<th>IA Signed-No Financial Security</th>
</tr>
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<td>2000</td>
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<td>57</td>
</tr>
<tr>
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<td>816</td>
<td>337</td>
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<td>2003</td>
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<td>1,305</td>
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<tr>
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</tr>
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</tr>
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<td>5,664</td>
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<td>4,403</td>
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<tr>
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**Notes:**
- The data presented here is based upon the latest information provided to ERCOT by resource owners and developers and can change without notice.
- Installed capacities for the current year account for changes reported by the facility owners during the reporting month, and will be reflected in subsequent years’ totals.
- Installed capacities include only wind facilities that have registered with ERCOT (Those larger than one megawatt and supply power to the ERCOT system.)
- This chart reports annual planned units with projected Commercial Operations Dates throughout the calendar year. In contrast, ERCOT’s Capacity, Demand and Reserves (CDR) report shows planned capacity projected to be commercially available on or before the start of the Summer and Winter Peak Load seasons.
- Financial security posted for funding interconnection facilities does not include CREZ security deposits, which are refunded to the Interconnecting Entity.

**Figure D2**: Hourly Market Share of the Four Biggest Producers in ERCOT
Figure D3: Monthly Average Wind Volatility. This figure shows the consistent increases in wind variance as more wind is integrated into the system. Wind variance is measured by the hourly variance in 15-minute wind generation. Monthly means of the variance show quadratic growth.
Figure D4: ERCOT Nodal Network Map
Figure D5: Network with and without Congestion
Source: ERCOT (http://www.ercot.com/content/cdr/contours/rtmLmp.html)

**Figure D6:** Settlement Point Prices in Day-Ahead and Real-Time Markets in ERCOT
Neural Network Architectures

In this section...

"One Layer of Neurons" on page 1-11
"Multiple Layers of Neurons" on page 1-13
"Input and Output Processing Functions" on page 1-15

Two or more of the neurons shown earlier can be combined in a layer, and a particular network could contain one or more such layers. First consider a single layer of neurons.

One Layer of Neurons

A one-layer network with \( R \) input elements and \( S \) neurons follows.

In this network, each element of the input vector \( p \) is connected to each neuron input through the weight matrix \( W \). The \( i \)th neuron has a summer that gathers its weighted inputs and bias to form its own scalar output \( n_i \). The various \( n_i \) taken together form an \( S \)-element net input vector \( n \). Finally, the neuron layer outputs form a column vector \( a \). The expression for \( a \) is shown at the bottom of the figure.

\[
\begin{align*}
\mathbf{a} &= \mathbf{f}(\mathbf{Wp} + \mathbf{b}) \\
a &= f(Wp + b)
\end{align*}
\]

(b) Multiple Layers with Multiple Neurons

This network can be used as a general function approximator. It can approximate any function with a finite number of discontinuities arbitrarily well, given sufficient neurons in the hidden layer.

Now that the architecture of the multilayer network has been defined, the design process is described in the following sections.

(c) Architecture of the Multilayer Network for Usual Function Approximation

**Figure D7:** Architecture of the Neural Network (Source: MATLAB Neural Network Toolbox User's Guide, MathWorks)
Figure D8. Regression of Prediction Results on Actual Targets – Fringe Firms
Figure D9: Prediction Errors for Day-Ahead and Real-Time Market Prices (October)
Appendix E

Equilibrium Behavior of the Biological Model for Chapter 2

In the deterministic case, the steady state population density \( N_\infty \) can be determined easily by first solving for equilibrium mean fitness \( \bar{W}_\infty \) given \( p_\infty \). This yields \( N_\infty = K \left( 1 - \frac{\min(-\ln \bar{W}_\infty, r)}{r} \right) \). For example, when \( p_\infty = 1 \) then \( \bar{W}_\infty = W_{RR} = e^{-\lambda} \) (given that \( v_t = 0 \) in the deterministic case), so that \( N_\infty = K \left( 1 - \frac{\min(\lambda, r)}{r} \right) \). Whereas if \( p_\infty = 0 \), then \( N_\infty = K \left( 1 - \frac{\min(\mu q_\infty, r)}{r} \right) \). In the threshold case of \( q_\infty = q^* \), we have \( \bar{W}_\infty = e^{-\mu q^*} = e^{-\lambda} \), so that equilibrium density is the same as in the fully resistant case. As noted in the manuscript, these results imply that when \( q_\infty > q^* \), then the pest population will be completely replaced by the resistant genotype. The long-run density of the total pest population in this case is \( K \left( 1 - \frac{\min(\lambda, r)}{r} \right) \). If fitness costs are positive, \( \lambda > 0 \), then this long-run density is less than \( K \), the wild-type population carrying capacity. This shows, as noted in the manuscript, that fitness costs can yield benefits in long-run pest density reduction, even after selecting for a fully resistant population.

When stochasticity is permitted \( (\sigma^2 > 0) \), the system in (2) amounts to a two-dimensional continuous-state, discrete-time Markov chain. Equilibria of such processes are determined via the kernel density \( \kappa(x_{t+1}, x_t) \), which is the probability density function for the next period state \( x_{t+1} := (N_{t+1}, p_{t+1}) \) conditional on the current period state \( x_t \). A stationary (i.e. equilibrium) distribution \( \pi(x) \) for the state \( x \) then satisfies the integral equation \( \pi(x) = \int \kappa(x', x) \pi(x') dx' \) (Stachurski 2009). As can be seen from (1) and (2), in our biological model \( \kappa(\cdot) \) involves a sum of correlated lognormal random variables which has no known closed-form solution. We therefore do not dwell further on analytic results for the equilibrium density \( \pi(\cdot) \).

However, three basic but important analytical results emerge from this model. First, \( N_t = 0, p_t = 0, \) and \( p_t = 1 \) are all permanent states in that, for example, \( \Pr[N_{t+1} = 0|N_t = 0] = 1 \). However, these states are all also trivial, in that they only occur with positive probability if we initialize the
system at such a state.\textsuperscript{8} Hence, the relative state space for analysis is $N \in (0, \infty)$ and $p \in (0, 1)$, i.e. pest densities and all genotype frequencies are always positive in nontrivial problems, even if sometimes infinitesimal. Second, the parameter $K$ can be thought of as a ‘carrying capacity in the median’ for a fully susceptible populations, in that $\Pr[N_{t+1} = K|N_t = K; q_t, p_t = 0] = 0.5$. The ‘carrying capacity in expectation’ can also be characterized using the first-moment formula for the lognormal distribution: $\mathbb{E}[N_{t+1}|N_t = K(1 + \sigma^2/2r); q_t, p_t = 0] = K(1 + \sigma^2/2r)$.

\textsuperscript{8} For example, $p_t < 1 \Rightarrow p_{t+k} < 1 \forall k \geq 0$. 
Appendix F

Parameterization for European Corn Borer Resistance to Bt Corn for Chapter 2

To parameterize our population genetics model using data from Hutchison et al. (2010), we begin as those authors do with the basic Ricker population model in the absence of resistance:

\[ N_{t+1} = N_t \cdot \exp \left( r \left( 1 - \frac{N_t}{K} \right) - \mu q_t + \epsilon_t \right) \]

Taking logs of this equation for linear regression analysis yields:

\[ \log \left( \frac{N_{t+1}}{N_t} \right) = r - \frac{r}{K} N_t - \mu q_t + \epsilon_t = \beta_0 + \beta_N N_t + \beta_q q_t + \epsilon_t \]  

(F1)

Consequently, assuming the shock \( \epsilon_t \) is uncorrelated with \( N_t \) and \( q_t \), linear OLS of the logged growth rate, \( \log \left( \frac{N_{t+1}}{N_t} \right) \), on lagged population density, \( N_t \), and Bt adoption, \( q_t \), produces consistent estimates of the regression coefficients, from which the population parameters can be imputed as \( r = \beta_0 \), \( K = -\frac{\beta_0}{\beta_N} \), and \( \mu = -\beta_q \). \(^9\) Though not reported by Hutchison et al., OLS also produces an estimate of \( \sigma^2 = \text{Var}(\epsilon_t) \), which is an important component characterizing stochasticity in our model. The estimate of these parameters for ECB in the U.S. is reported in Table 1.

The only biological parameters missing from this estimation are those specifically related to Bt resistance in our model: the fitness cost \( \lambda \), the correlation \( \rho \) between the population shocks, and the dominance \( h \) of the resistant allele. Because \( \lambda \) is the central parameter of interest in our AM application, we do not set a specific value for this parameter. However, we must specify a reasonable range for numerical computation of the value functions. The correlation parameter \( \rho \) determines the degree of orthogonal variation between the environmental shocks \( \epsilon_t \) and \( \nu_t \) for

\( \rho \) $\ldots$ This specification is essentially same as the regression model estimated by Hutchison et al. and produces nearly the same estimates, except that in their model \( \log N_t \) appears on the right-hand side instead of \( N_t \). While both specifications are sometimes referred to as Ricker models, our specification is more standard in the literature, and converges to logistic growth as the limit of the time step goes to zero. Also, even though the EPA’s refuge mandate has been effectively fixed since the widespread introduction of Bt crops, \( q_t \) has enough variation for identifying \( \mu \) in the OLS regression in eq. (22) due to the dramatic increase in Bt adoption over the period analyzed by Hutchison et al.
the susceptible and resistance subpopulations, respectively. If \( \rho = 1 \), then there is no orthogonal variation in the subpopulations. With no real data on this parameter for our example application, we begin by setting it equal to 0.5, supposing that a significant amount of stochasticity in ECB populations is common to all genotypes, but also a significant amount of independent variation between the subpopulations. In sensitivity analysis below, we vary \( \rho \) to see how it affects the results from our analysis. In reality, uncertainty in \( \rho \) would imply another parameter to be subjected to adaptive management. In contrast to \( \lambda \), there are unlikely to be convenient analytical conjugates yielding closed-form posterior distributions for \( \rho \), implying the need for computational methods for approximating the posterior distribution of \( \rho \) (e.g. such as the density projection method introduced by Springborn and Sanchirico 2013). Given that the present paper is the first to address adaptive management of resistance, we assume a fixed \( \rho \) for now. Existing evidence on the dominance of Bt resistance in ECB suggests that resistance genes in this organism are recessive (Gassmann, Carrière and Tabashnik 2008), and so we set \( h = 0 \).
Appendix G

Figures for Sensitivity Analysis with respect to \( \rho \) for Chapter 2

Figure G1: Value of Information across Management Regimes for Selected Case Studies (\( \rho = 0.75 \))
Figure G2: Value of Information across Management Regimes for Selected Case Studies ($\rho = 0.25$)
Figure G3: Value of Information across Management Regimes for Selected Case Studies ($\rho = -0.5$)