

Negative Wholesale Power Prices: Why They Occur and What to Do about Them

by

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Abstract

The concurrent deregulation of the German power market and increased percentage of electricity generated using intermittent renewables have resulted in the occurrence of significantly negative wholesale power prices and increased overall price volatility. Many studies of methods to curb price volatility suggest that dynamic pricing may be part of the answer. However, few studies have analyzed the resulting consumer price response behavior in the context of intermittent renewables and the subsequent negative prices that have become more common as the use of renewables has increased. This study serves as a preliminary attempt to evaluate the effects of dynamic pricing on negative prices. Using a set of hours from the year 2009, chosen to represent different levels of demand and wind in-feed, and a linear demand curve that can be used to model demand when prices are negative, I compare price changes resulting from increases in wind in-feed and the implementations of dynamic pricing mechanisms. Using this methodology, I find that without a significant level of consumer prices elasticity, dynamic pricing may not be beneficial and in some cases even harmful to market efficiency. Based on these comparisons, I make recommendations for further research to define policy measures for the successful deployment of demand side management techniques such as dynamic pricing.

1 Introduction

On Sunday October 4, 2009, at approximately 3:00 AM, the German Power Exchange (EEX) registered a day-ahead market clearing price of -500.02 €/MWh (EEX). No, the negative sign in front of the price per MWh is not a mistake. In fact, this occurrence marked the 71st time that the price for electricity dropped below 0 €/MWh since the EEX removed the price floor in September 2008 (Nicolosi, 2009). Essentially, during this hour, generators paid consumers to use electricity. Such a phenomenon seems counterintuitive and contrary to the theories governing commodity markets. However, electrical power fails to conform to the standard commodity market model in many respects. First and foremost, unlike most physically tradable commodities, electricity cannot be stored easily. As such, in power markets, generated supply must constantly be equal to demanded load, creating the opportunity for rapid price shocks due to disparity between expected supply and demand quantities. Secondly, in most commodity markets, consumers make consumption decisions based on the market price. In electricity markets, the public does not reduce their consumption when supply becomes tight and prices rise, or conversely raise consumption when there is excess supply and wholesale prices fall, simply because they are not subject to the wholesale price difference in the short term.

Traditionally, wholesale market participants and regulators have been concerned with extreme price increases and techniques for mitigating them. But, system flexibility becomes an issue in times with both very high or very low demand. In either case, the market shows wholesale power prices which deviate from the usual pattern (Cramton, 2004; Ockenfels et al., 2008). In times with very high demand, the market occasionally shows prices above variable cost of the power plants, while in hours with very low demand, the market shows prices below variable costs (Nicolosi, 2009).

Experts have generally not concerned themselves with controlling extremely low prices, since they are not harmful to the market in the same way that high prices are. High prices are indicative of a market that has the potential for a systemic blackout and as such, it is extremely important to monitor them and devise ways to reduce them. However, the proliferation of RES-E has seen increased shocks in the other direction, eventually leading to negative prices on the same order of magnitude as positive shocks, albeit occurring significantly less often (Genoese, 2010). While the occurrence of negative

prices is an extreme example of how the integration of RES-E has affected the electricity market at the margins, intermittent renewables also have an overall effect of lowering prices in any hour that they are deployed. While this may be a positive outcome for electricity consumers, overall price volatility within all hours of generation also increases with the inclusion of intermittent renewables due mostly to the unpredictable nature of natural resources like wind and sunlight (EWEA).

Many industry experts have advocated the use of dynamic pricing schemes, where wholesale prices are transferred to end-users, to control for drastic price increases and smooth the long run price curve (Borenstein, 2005; Mansur and Boisvert, 2007; Spees, 2008). The theory behind dynamic pricing suggests that it be employed to reduce overall price volatility. However, the effect dynamic pricing mechanisms will have on price volatility caused by intermittent renewables remains largely unknown, with much speculation but relatively little analysis (Nicolosi, 2010; Connors, 2010; EWEA). This is due mainly to the fact that RES-E impact the lower supply margin and thus have the largest impact on prices when demand is low, while studies of dynamic pricing have been concerned with price effects when demand is high.

The remainder of this introduction is structured as follows: First, the German power market is introduced in the context of the occurrence of deregulation and the coincident emphasis on the integration of renewable energy sources (RES-E). The next section discusses the need for demand side flexibility in deregulated, competitive power markets, which can be achieved in part by dynamic pricing mechanisms. The third section introduces the concept of the merit order effect and discusses its implications on the supply side of the power market when wind power is introduced. The fourth section explains in greater detail the reasons for negative prices and the role of wind power in their proliferation. In the last section, I will introduce my research, which seeks to understand the conflux of these emerging market changes, defined on the supply side by the increase in intermittent renewable – specifically wind power – and the subsequent rise in the occurrence of negative prices and on the demand side by deregulation and a shift towards a competitive market.

1.1 German Power Market

Germany is Europe's largest power consumer, with a total annual consumption of nearly 560 TWh (ENTSO-E, 2010), as well as the largest wind power market in Europe, in absolute terms (EWEA, 2010). The German power market is divided into two primary market structures, an over the counter (OTC) market and the European Energy Exchange (EEX) located in Leipzig (ENTSO-E, 2010). The EEX market that I focus on is a single auction, day-ahead spot market that settles at 12:00 PM on the day before physical delivery of the purchased electricity. The OTC market, on the other hand, is characterized by continuously traded, bilateral contracts between generators and utilities (Strecker, 2001).

Prior to deregulation, only about 7% of Germany's electricity was traded in day-ahead auctions (Strecker, 2001). While OTC bilateral trading remains the dominant market mechanism, in 2008, the total volume of electricity traded through the EEX reached 145.6 TWh out of an annual total German electricity consumption of 557.2 TWh (Genoese, 2010), for a respectable 26% of market share. Additionally, although nearly 75% of trading is settled via bilateral contracts, the EEX day-ahead spot price can be considered the benchmark for OTC contract pricing. Due to the opportunity for arbitrage in the EEX market, price expectations for OTC buyers and sellers cannot deviate from the expected clearing price of the EEX day-ahead auction. A buyer wouldn't enter an OTC contract if the expected outcome of the EEX were more beneficial. Consequently, expected prices in the EEX can be systematically expected to determine the value of OTC contracts, barring the risk hedging premium on long term bilateral contracts. So, while only 25% of traded volume is directly determined by EEX auctions, the clearing price implicitly affects the OTC market. An analysis of price volatility in the EEX day-ahead market, therefore, can be reasonably extended to the whole power market.

The issues surrounding implicit wholesale price volatility in electricity markets have been exacerbated by the liberalization of the traditionally state-supported, vertically integrated power markets that characterized most of the western world prior to the 1990s. Before deregulation, electricity generation, transmission, distribution and sales were all accomplished by a single vertically integrated utility, allowing all price setting decisions to be made with complete transparency by the utility price setters. Deregulation of the German power market began following ratification of the German Energy Industry Law (hereafter referred to as EnWG) in April 1998; the main goal of the new law being "to achieve a safe, reasonably-priced and ecological-oriented energy supply for the public benefit" (§1 EnWG). Liberalization of the vertically integrated power industry created a competitive market for generation and retail sales, while leaving naturally monopolistic transmission and distribution under government regulation. Transmission and distribution have remained highly regulated as a result of being natural monopolies due to high barriers to entry and exorbitant capital costs of constructing transmission and distribution systems. Generation and retail sales, however, have been unbundled from the other facets of the

supply chain and induced into a competitive market structure. The logic behind this action being that competition in generation and sales would result in lower prices and a more efficient allocation of generation resources. However, singular focus on the improvement of competition in the market's supply side and asymmetrical market power between the suppliers and demanders has hindered efficient operation in liberalized markets.

In addition to addressing liberalization, the EnWG subsequently provided provisions for the promotion of renewable energy sources (RES-E) (§1 EnWG). Two years later, the Renewable Energy Sources Act of 2000 (EEG) created the means for their integration into the market by requiring energy suppliers to purchase a portion of their load from renewable generators at prices influenced by predetermined feed-in tariffs (FITs) set by the EEG (§3, 4-8 EEG). Guaranteed FITs have been in place since 1991, but revisions to the renewables support scheme in 1998, 2000 (EEG), 2004, and most recently in September 2010 have been responsible for the considerable growth of renewables in Germany over the past 15 years (Sensfuß, 2008). FITs function to bring renewables into the market in two stages: First, grid operators (TSOs) are required to purchase electricity generated by renewable energy sources at a guaranteed feed-in tariff. Then, the electricity is sold to retail suppliers according to their market share (Genoese, 2010) either through OTC contracts or in day-ahead EEX auctions at a price reflecting the additional cost of the FIT.

As of January 1st, 2010 TSOs are able to sell all renewable electricity directly on the spot market, meaning that the increased saturation of RES-E in the market could lead to further price volatility in the future. This analysis can only suggest this outcome based on previous research on the price impact of RES-E (EWEA; Nicolosi, 2009; Genoese, 2010; Sensfuß, 2008), since not enough data exists in the short period of time since this change occurred to conduct a meaningful analysis. For that reason, the following analysis of price response will consider only the time period from January 2009 to December 2009 and induce an artificial increase in wind during one iteration of the analysis to suggest what may happen to the market as wind penetration increases.

1.1.1 The Demand Side and Pricing Mechanisms

Traditionally, retail demand for electricity is assumed to be inelastic, since without access to real-time pricing information, end-users will continue to demand electricity even when price exceeds their true willingness to pay (OECD, 2004). This, coupled with the fact that prices for end users are held constant throughout the day, creates asymmetry of market power that impedes efficiency and contributes to the need for expensive peaking power plants and large spinning and non-spinning reserves. Inelastic retail demand places the entire burden of uncertainty on the supply side, since generators must meet demand under any scenario – regardless of generation capacity constraints – or face a systemic failure like blackout. The disconnect between the wholesale and retail markets creates an inefficient use of generating resources. The result is that systems planners require additional expensive and inefficient capacity be built to maintain a low likelihood of capacity shortages (Spees, 2009).

In most deregulated markets, retailers utilize a schedule of flat rate tariffs, sometimes accompanied by capacity charges and peak load factors (which apply mostly to large commercial and industrial end-users) for pricing. Customers pay a flat rate for electricity no matter when they consume it, even at times of peak demand when wholesale prices explode upward and increased stress on the grid threatens system stability or at times when wholesale prices are extremely low and end users grossly overpay for their electricity. Because of the lack of transparency and overall increases in demand for electricity over time, stress is placed on the transmission grid, and the likelihood of black- or brownouts increases.

While retail markets face little to no short-run price volatility, the story is drastically different in the wholesale generation market. Because of electricity's unique nature as an unstorable commodity, the need to have real time supply constantly equal demand creates conditions where extensive price volatility exists. Since electricity must be consumed at almost the instant it is produced, any large fluctuations must be accounted for by supply capacity. Extreme weather conditions and transmission constraints exacerbate price shock behavior and seasonal fluctuations add further complexity to wholesale pricing structures. In addition, while in most markets baseload electricity is generated using inexpensive and price-stable fuel inputs, generators with high marginal costs generally produce peaking load. Variation in the marginal costs of peak load electricity translates directly into more variable wholesale prices. Since retail prices do not capture fluctuations in the wholesale price, volatility in the wholesale market can negatively affect the market as a whole, creating instability and the potential for systemic outages.

In an hour when demand is high, the retail price consumers face is below the actual marginal cost that the producers incur from generating the electricity, which results in a deadweight loss for the market. The same is true in an hour when demand is low, though in this case the deadweight loss results because the retail price is above the producers' marginal costs. *Figure 1* illustrates that deadweight losses occurring from the disconnect between wholesale and retail prices.

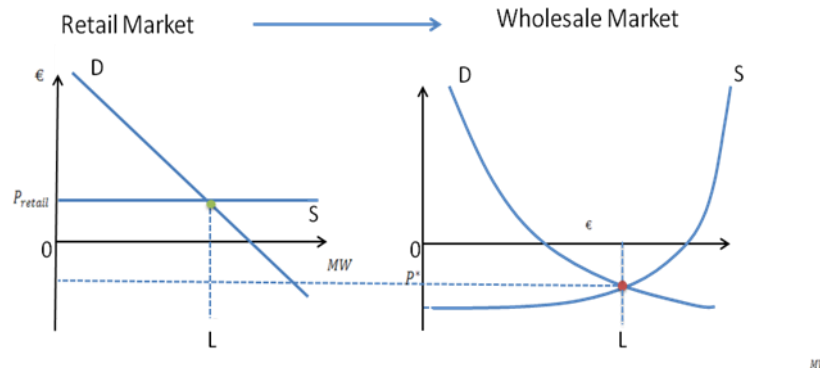


Figure 1: Deadweight losses resulting from the difference between wholesale and retail prices

Many economists and power industry experts advocate the implementation of dynamic pricing mechanisms to correct for the inefficiencies resulting from a retail flat rate tariff schedule. Theoretically, dynamic pricing involves the direct and complete transfer of wholesale market prices to the retail market in real time. In practice, however, dynamic pricing can take a variety of structural forms, the most common being Real Time Pricing (RTP), Critical Peak Pricing (CPP), and Time-of-use Pricing (TOU). RTP schemes, closest in level of dynamism and transparency to a true dynamic pricing system, involve end-users being charged lagged wholesale prices from either the previous day or previous 5-30 minute increment. TOU pricing involves setting different price tariffs for previously decided peak and off-peak time periods for a duration set in advance of the time period. Generally peak hours are defined as Monday-Saturday work day hours and off-peak are defined as night and Sunday hours, as well as pre-designated holidays. CPP is similar to TOU pricing; however, it additionally reflects wholesale prices for a set of pre-announced “peak days” when electricity prices are expected to be especially high. For instance, blocks of days that are expected to be especially hot may be peak days, since demand can be expected to be quite high due to the increase in air-conditioning.

Implementing dynamic pricing would alleviate the capital and variable input costs of peak load generation. Expectations of higher prices in hours of high demand would drive demand/price down and peak load capacity could be taken offline. Under the same logic, at the low end of the marginal cost curve, expectations of low-to-negative prices in hours of low demand would drive prices up. Dynamic pricing would also lessen the severity of deadweight losses in the market by driving retail prices closer to the wholesale price, with the magnitude of the price response depending on consumers' price elasticity. Therefore, such a market change could reduce the severity of price shocks – at both extremes – and smooth the price curve in the long-run.

1.1.2 The Supply Side Merit Order Effect and Wind Power

Generally, when an electricity market model is defined, the total electricity supply is represented by a merit order curve. Under the merit order principle, power plants with the lowest marginal costs are used first to meet demand, with more costly plants being brought online later if needed. (World Future Council, 2010) Hydroelectric, nuclear and coal power plants have relatively low marginal costs and are generally used for baseload generation under this principle. Natural gas, in the form of combined cycle gas turbines (CCGT) and basic gas turbines (GT), is used as peaking generation due to the high variable cost of natural gas.

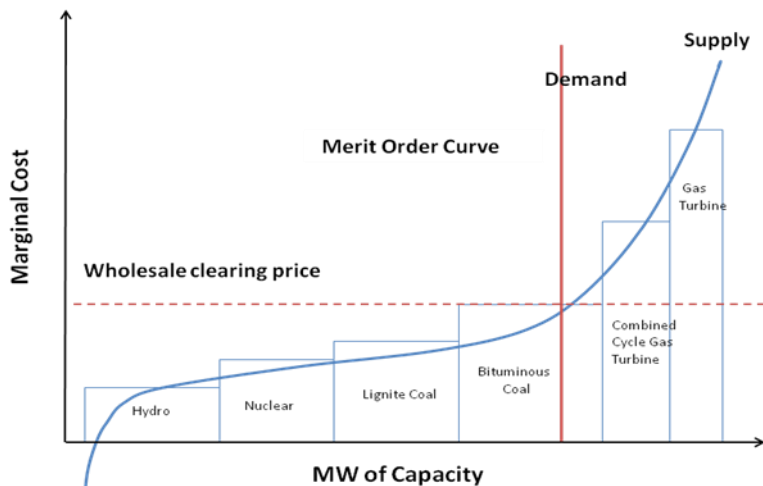


Figure 2: Merit Order Curve without Wind Generation

Figure 2 shows the traditional merit order curve without any RES-E generation. The curve is constructed by stacking the marginal costs of each generation type. Since hydro power has the lowest marginal cost it enters the leftmost portion of the supply curve and is the first generation type dispatched to meet demand. At the other end of the spectrum, gas turbines with the highest marginal cost enter the rightmost portion of the curve and are only dispatched if the level of demand is particularly high.

The merit order curve has recently been subject to lateral shifts due to the integration of renewables onto the grid. This is because wind power is capital intensive in terms of start up costs; however, with no need for fuel inputs, its marginal cost is nearly zero. Due to this characteristic, when dispatched, wind power will enter the merit order curve and move it rightward as seen in Figure 3.

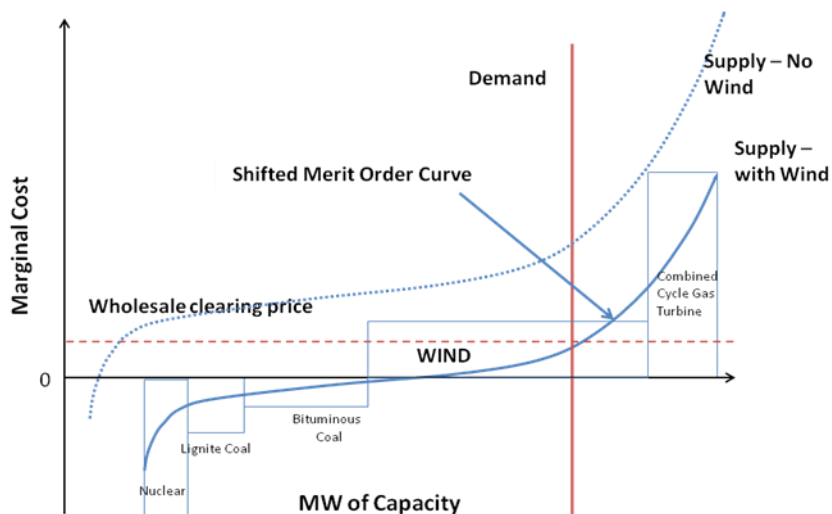


Figure 3: Merit Order Curve with Wind Generation

This means that the marginal cost of production required at each level of supplied power will be lower than if wind power were not available, i.e. wind power displaces the most expensive power source that would have been needed otherwise, typically a gas-fired plant. The most expensive conventional power plants, i.e. gas turbines, are therefore no longer needed to meet demand and will shut down. If the FIT is lower than the price from the most expensive conventional plants, then the

average cost of electricity decreases, and this is called the merit-order effect of intermittent renewables. Because renewable electricity must be purchased before other sources, the size of the remaining demand for which electricity must be purchased on the spot market is reduced. (World Future Council, 2010)

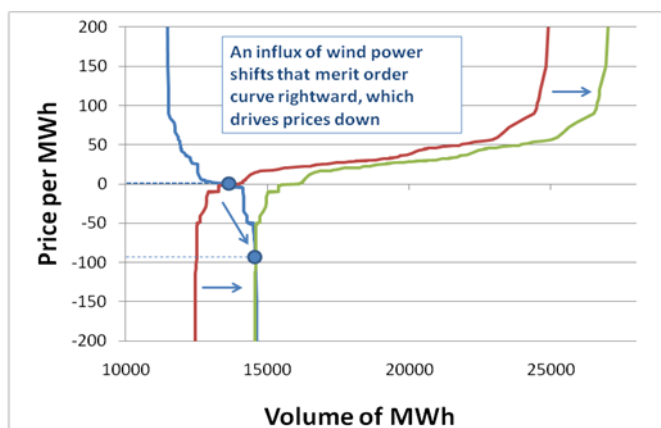


Figure 4: Actual Supply and Demand Curves showing the impact of the merit order effect of wind power on the wholesale power price

Wind generation is the most technologically developed renewable and the most widely in use today. Germany has an installed wind capacity of 25,777 MW, which accounts for approx. 22.5% of all generating capacity. In fact, wind power has the single largest capacity of any generation type in Germany, followed by lignite coal with an installed capacity of 18,776 MW (BMU). In 2008, nearly 40 TWh of Germany's electricity consumption was satisfied by wind generation for a market share of approximately 6.3% (BMU). Further, the Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit (BMU) projects that Germany will double its installed wind capacity by 2025, bringing the total to almost 51 GW. While projections for other RES-E also predict an increase, wind capacity can be expected to have the most significant market impact due to the size of its market share. Furthermore, the integration of wind generation into the German power portfolio to date has already created an impact on prices in the power market (Sensfuß, 2008; Genoese, 2010; Nicolosi, 2010). Thus, my analysis will specifically evaluate the impact of wind capacity, since its impact can be more easily derived due to its relatively large market share as compared with other RES-E.

Since wind is an intermittent natural resource, the power market reacts strongly to the stochastic nature of wind power in-feed. In times of high wind in-feed, the spot price in the wholesale market tends to be lower, compared to times without wind power in the system (Nicolosi, 2010). The intermittency of other renewables such as solar may cause volatility and potential sporadic negative pricing, especially as the technology improves. However, there is especially little correlative behavior between times of peak wind production and peak electricity demand, creating greater opportunity for negative pricing to occur. In fact, the peak and trough of the daily wind electricity production cycle is exactly out of sync with the peak and trough of the daily demand cycle in many regions (Frank and Wolak, 2010).

1.1.3 Negative Prices

The phenomenon of negative pricing occurs when the supply of electricity temporarily exceeds the demand. During these periods, baseload generators, like coal, prefer to stay running and pay to put their electricity on the grid by placing negative auctions bids rather than take their generators offline and incur high ramping costs when demand goes back up. The cost of paying end users to consume their electricity is less than the ramping cost of restarting their turbines. Specifically considering the role of wind generation in the occurrence of negative prices, a study conducted by Nicolosi found that in times of high wind power in-feed and low demand, the market reacts with bids underneath variable costs in order to avoid ramping-down base load power plants, which are expensive to restart. (Nicolosi, 2010) This phenomenon resulted in the occurrence of 71 hours of negative prices in Germany in 2009.

While the manifestation of negative prices may seem counterintuitive to the laws governing commodity markets, the rationale for allowing negative prices is that it creates a more efficient, competitive supply side (Nicolosi, 2010). However, the increased competition allowed on the supply side is undermined by the lack demand side flexibility. Currently, negative prices are reflected as rebates to end users on their monthly bill. Under a flat rate pricing scheme, consumers don't have any

information about when hours of low prices might occur. As such, they can't make any decisions about altering their consumption patterns to take advantage of the low priced hours.

Thus the potential impact of negative pricing on resource adequacy remains one of the most pervasive issues related to variable renewable energy sources and competitive market design (Smith, 2010). Negative wholesale power prices serve as a market signal for additional requirements that target system flexibility. In the presence of climate policy legislation and the desired RES-E increases that Germany seeks to attain by 2025, managing the price volatility inherent in intermittent RES-E is going to play an increasingly important role in the power system. As such, demand side flexibility within power systems is becoming increasingly important (Nicolosi, 2010).

1.2 Changing Power Markets

If this was a static system, one could argue that limiting of wind power in-feed during low demand hours would be the solution to extreme price dips. However, having the dynamics of the power system evolution in mind, it becomes apparent that this approach is short-sighted, as it reduces the market signals that reward flexibility and facilitate the necessary structural changes which will promote the diversification of the generation portfolio (Nicolosi, 2009). Because Germany has a goal of aggressively increasing the amount of electricity generated by renewables, any method to increase system flexibility will most likely have to come from the demand side of the market rather than the supply side.

It has been suggested that one way to mitigate the imbalances of negative pricing is to implement a dynamic pricing scheme (Cailliau, 2010; Smith, 2010; Nicolosi, 2009). This idea, however, has not been evaluated empirically. I intend to begin a preliminary analysis by building on prior works that model consumer price response under RTP schemes in markets that use primarily fossil fuels.

This paper will focus strictly on RTP as my purpose is to understand generally the relative magnitude of price response induced by dynamic pricing in a market that allows negative prices, rather than make suggestions about implementation, since structural decisions can be made only in the context of specific power markets. In addition, since RTP most closely mimics the characteristics of a true dynamic market, it will provide the clearest, most intuitive results. The aim of this paper, then, is to demonstrate the effects of employing dynamic pricing models in a competitive market with extensive capacity generated using intermittent renewables, where intermittent renewables are defined as carbon emission free energy sources for which supply cannot be generated constantly or consistently. In a market with significant renewable energy penetration, day-to-day prices are likely to be more volatile, and price volatility is likely to result from changes in renewable energy availability (e.g., large wind ramps) rather than exclusively due to demand fluctuations (Smith, 2010). Specifically, this study is interested in price volatility resulting in negative prices.

2 Literature Review

Exploring the existing literature on these topics, this review first focuses on research that has developed around the use of dynamic pricing to improve demand side flexibility. Then I turn to research that is emerging about the integration of intermittent renewables within the existing power system framework.

2.1 Dynamic Pricing Literature

Extensive research has been done to analyze the impact of varied dynamic pricing models on end user demand. Studies of short-term effects on own price elasticities and elasticities of substitution have delivered varying results. Spees reports a short run elasticity range of 0.05 to 0.4 using observed market prices, which account for transmission and other constraint costs, to construct her supply curves (Spees, 2008). While Holland and Mansur, creating a constant supply stack derived directly from marginal costs, assuming constraint free generation capacity dispatch, report elasticities nearly half of Spees' (Holland and Mansur 2004, 2006). Studies of program results from Niagara-Mohawk Power Corporation's default RTP for customers larger than 2 MW returned an average demand elasticity of substitution of 0.11 (Boisvert, 2007; Neenan, 2004). A Department of Energy study found price elasticities of substitution in the range of 0.02 to 0.27 under TOU, critical peak pricing (CPP), and day-ahead RTP situations (DOE, 2007). Braithwait and Sheasy produced similar results in an analysis of Georgia Powers RTP program, giving a range of 0.01 to 0.28 (Braithwait and Sheasy, 2002). Meanwhile, Frank and Wolak return a short run range of 0.001 to 0.25 in their study of price response in industrial customers in the United Kingdom (Frank and Wolak, 1997). Furthermore, Borenstein's estimation of long-run elasticities produced a range between

0.3 and 0.5 suggesting that over time consumers will become more price responsive (Borenstein, 2005). Some of the studies were conducted using simulated dynamic markets (Borenstein, 2005,=; Spees, 2008) and other evaluated the results of implemented pricing programs (Frank and Wolak, 1997; Braithwait and Sheasy, 2002; Boisvert, 2007; Neenan, 2004); but they all analyzed markets where the fuel inputs were primarily fossil fuels.

From these elasticity ranges, the respective studies calculated consumer savings, as well as changes in consumer and producer surpluses to determine the effects of price responsive demand on market efficiency. All of the studies indicate that even with low levels of price elasticity, small changes in peak demand would create significant savings for consumers. Regardless of the variation in savings values, these results add compelling resonance to the argument for implementing dynamic pricing schemes in liberalized markets. It is, therefore, generally accepted among economists that theoretically, utilizing current standard generation technology, dynamic pricing has the ability to mitigate market inefficiencies that result from flat rate tariffs.

2.2 Wind Power Literature

As wind generation has proliferated in power markets, so has the literature addressing it's role within current market structures. There have been a number of recent papers analyzing the effect of wind generation on spot market prices, some which create market simulations and others that look at historical trends. Sensfuß simulates spot market prices with and without wind generation and measures the merit order effect on spot market prices. The merit order effect, which is the price differential that occurs when the supply curve shifts rightward due to the influx of wind in-feed during a particular hour, shows a reduction in the average market price of €7.83/MWh in Germany in 2006 (Sensfuß, 2008). Other studies have analyzed how the intermittency of wind has affected prices. In one such study, Nicolosi uses a statistical model and historical data to find a negative correlation between wind power in-feed and power prices.

Additionally, analyses of markets currently employing wind capacity have uncovered a trend counterintuitive to traditional commodity market behavior – negative pricing. In an analysis of wind generation in ERCOT, Baldick found that West Texas wind is anti-correlated with ERCOT demand since the wind tends to blow more in winter, spring, and autumn than in summer, whereas peak demand in ERCOT, driven by air-conditioning, is highest in the summer and more during off-peak hours than on-peak (Baldick, 2009). From this, Baldick's case study found that in 2009 there occurred 3069 fifteen minute intervals when prices dropped below \$0 (Baldick, 2009). A similar analysis of the German market revealed 86 hours of negative prices from September 1st 2008 to December 1st 2009 (Genoese, 2010). Among those, 19 hours had significantly negative prices under 100 €/MWh (Genoese, 2010). Again, an inverse relationship between wind in-feed and demand was found. During all 86 hours, it was found that a necessary condition for negative prices appeared to be either high wind in-feed (>12 GW) coupled with moderate system demand (40-50 GW) or low system demand (<40 GW) coupled with moderate wind in-feed (5-10 GW) (Genoese, 2010).

Negligible attention has been paid to the interaction of renewable integration and demand side in power markets, specifically when considering the occurrence of negative prices. Connolly looks at the conjoint affect of RTP and intermittent renewable on emissions and producer revenues, but focuses mainly on the political economy of such decisions (Connolly, 2008). Also, the New England market that he evaluates has a much smaller penetration of wind than the German market and smaller targets for increases. A larger market penetration will provide more significant results, as increases in wind generation are predicted to have increasingly large effects on price volatility, leading even to negative prices which are not yet seen in New England due to the relatively low existing wind capacity and existing price floors.

My work will build on the preliminary work done by Connolly by evaluating the effect of RTP on the negative prices resulting from the influx of wind generation that are becoming increasingly common in the German market. As the penetration of RES-E increases in the market, so too will the conditions that lead to potential negative prices. As such, having an understanding of price response within these hours is important for maintaining a robust and efficient market. My analysis serves as a preliminary attempt to understand consumer price response given these factors.

3 Data

For this analysis, the German power market was chosen due to both its market characteristics and the robustness of the data available. Because of its broad technology mix coupled with substantial wind penetration, the German power market is a good example for an investigation of power system flexibility (Nicolosi, 2010). Additionally, the German market is ideal

for this analysis because pricing in Germany is based on a single auction clearing value across all zones, which allows the analysis to abstract away from the issue of negative pricing due to transmission constraints. The complication of transmission constraints is an issue in U.S markets with high wind penetration and zonal pricing, like the Electric Reliability Council of Texas (ERCOT). By choosing a market where zonal pricing is not a factor, no assumptions need be made about whether negative prices are due purely to generation characteristics or transmission congestion.

The data for this analysis comes from a variety of sources to create a complete picture of the German power market. I construct supply curves, demand curves, and solve for market clearing price and volume based on historical data. Data for generator bids, as well as market clearing price and volume, comes from the European Power Exchange EPEX Spot historic market database. The realized wind power in-feed comes from the four German TSOs, (50 Hertz, Amprion, EnBW and TenneT), summed together to form a system-wide in-feed value. Since this paper analyses a real market scenario using historical data, realized wind in-feed is used and modified to simulate an increase in capacity, rather than estimation methods that employ wind forecasts to determine in-feed values. Average retail prices are estimated using revenue and consumption data from the annual reports of Germany's four largest utilities: EnBW, E. On., Vattenfall, and RWE AG.

My research focuses on the time period from January 1st, 2009 to December 31st, 2009. I chose this time period because it contains the most current full year cycle of data available during which negative prices were allowed and in which wind capacity is highest. Also, due to the change in RESE-E infeed regulations after January 1, 2010, I exclude the time frame after this date in order to analyze only hours in which regulations governing RES-E infeed were consistent.

4 Model Specifications

Using the historic market data, I first construct supply and demand curves for a set of hours that represent different combinations of market conditions. The four combinations are as follows: high demand, high wind infeed; high demand, low wind infeed; low demand, high wind infeed; low demand, low wind infeed – the hours being chosen to take into account the thresholds laid out in Genoese's study. For the purposes of the investigation of price response to negative prices, I focus the analysis on the hours when demand was low, since these are the hours in which wind infeed has the potential to generate extremely low prices. The other hours of high demand are used for comparative purpose to give a relative scale of the magnitude of expected price response.

Once the base case curves are mapped and the existing market clearing price and volume are determined, 3 different scenarios will be examined:

(M1) the market with existing price structure and increased wind penetration

(M2) the market with induced dynamic pricing and existing wind penetration

(M3) the market with both dynamic pricing and increased wind penetration

In order to facilitate a straightforward, transparent analysis, I make the following assumptions about the model. First, I assume that bids into the EEX reveal the marginal cost of generation for the MW plus the value of feed-in tariffs for renewable generation, conditional on the assumption that no market power is exercised, as this is a competitive auction. Second, I assume demand elasticity is not constant, allowing me to utilize a linear demand curve. My analysis makes no assumptions about consumer behavior, other than to say that consumers are rational and, as such, make their decisions about consuming electricity as they would any other commodity. While I don't make any particular assumptions about behavior across hours, I note that an average consumer is unlikely to react to price fluctuations during late night and early morning hours the same way they would during daytime hours for practical reasons. This is why my analysis uses a range of elasticities as estimated in previous studies to represent different levels of price response. For the purposes of designing policy instruments that would implement a dynamic pricing scheme, deriving an intimate understanding of consumer behavior across different time periods is crucial. However, for the purposes of my research, such a rigorous analysis is beyond my scope.

4.1 Supply Curve Construction

Turing first to the construction of the supply curves: the marginal costs associated with the EEX generator bids create the merit order curve which illustrates the level of supply available by each generation technology at a specific price. To model the curves, I sort the bids by increasing value per MW so that the generator with the highest cost per MW will be last. I then determine the total additive volume of MWh (L_i) when price is less than (P_i) for each $i = 1, \dots, n$. Finally, to construct the merit order curve, the sets of points (L_i, P_i) are plotted for all $i = 1, \dots, n$.

Next, I determine the auction-clearing price under the current flat rate tariff, using the actual observed traded load for the hour (L^*) to locate the wholesale market price (P^*). Then, I determine the yearly average retail tariff using annual sales revenue and total annual kWh consumed.

$$P_{\text{retail}} = \frac{R_{\text{yearly}}}{L_{\text{yearly}}}$$

The actual tariff rate paid by customers varies by the customer's rate class. However, using this method, I derive an average price across all rate classes.

4.2 Demand Curve Construction

Next, I construct estimated retail demand curves. Studies of dynamic pricing have traditionally used an exponential demand function:

$$P = \beta L^{\frac{1}{\epsilon}}$$

where ϵ is the elasticity of demand, L is the load volume of MWh, P is the price and β is the load factor coefficient. This model is a generally agreed upon method of electricity demand modeling (Spees, 2009; Borenstein, 2005; Frank and Wolak, 1997).

However, analyzing consumer behavior when prices are negative is particularly challenging. Typically, electricity demand is modeled using a constant elasticity demand function. But demand functions with constant elasticity can't be defined for prices less than or equal to zero due to the exponential functional form that demand takes. Since economic principles stipulate that demand is not defined when prices are negative, theoretically this functional form is appropriate. Intuitively, this rationale makes sense because in a traditional commodity market with sticky prices, if prices were ever negative, or a good were essentially free, people would consume as much as they could, up to a saturation point or the limit of the supply. However, often real life situations fall outside of the laws that govern economic theory. I've already described a number of ways in which electricity does not follow the behavior of a traditional commodity and the allowance of negative prices is yet another exception to the rule.

In order to move away from this limiting factor, I use a linear demand function for my analysis that will allow me to evaluate the effect of RTP on negative prices. My function has the following simple form:

$$P = \alpha - \beta L$$

where the slope, β , is determined for each demand curve by solving the following point elasticity equation (1) for $\left(\frac{dL}{dP}\right)$. This is accomplished by plugging in the existing flat rate retail price and volume and the chosen price elasticity into equation (1) and taking its reciprocal (2):

$$\epsilon = \left(\frac{dL}{dP}\right) \frac{P_{\text{retail}}}{L^*} \quad (1)$$

$$\beta = 1 / \left(\frac{dL}{dP}\right) \quad (2)$$

Then, to solve for the intercept α , I plug the retail price and volume into (3):

$$\alpha = L^* - \beta P_{\text{retail}} \quad (3)$$

Each demand curve can then be plotted around the existing equilibrium point for its respective price elasticity, ϵ . The base case model assumes that $\epsilon = 0$ and therefore the demand curve is inelastic and is represented by a vertical line where the traded volume remains constant at each price level.

4.3 Mapping the Scenarios

The first scenario (M1) assumes the same inelastic demand curve as the base case model, but shifts the supply curve by creating an artificial increase in wind capacity. My model increases the amount of wind generation by 50% of the existing percentage of generation currently coming from installed wind capacity. The wind infeed data I obtained is for the whole German grid and not simply the amount traded in the EEX auction, so I increase the amount of generation first by determining the wind percentage of total German load. Then, assuming that the ratio of wind MWh to total load traded on the EEX is the same as the system wide ratio (4), I calculate the estimated number of EEX wind MWh.

$$\frac{\text{Total Wind Infeed}}{\text{Total Load}} = \frac{\text{Wind in EEX}}{\text{EEX Traded Volume}} \quad (4)$$

After determining the percentage of MWh traded on the EEX, I take 1.5 times the percentage, determine the value of additional MWh and add that value to the original volume for each price level in the supply curve. Using the shifted supply curve, I then determine the new clearing price that would occur under a flat rate tariff if wind infeed were to increase by 50% within that hour, assuming no other generators take their capacity offline. In reality, this increase in wind capacity would likely not shift the supply curve as drastically as my calculations indicate because other generation types could potentially adjust their system infeed. However, without accurate wind forecast models, it will be difficult for generators to correctly predict how they should react. In this case, they are likely to either over- or under- predict their infeed adjustment and thus hours with a drastic supply curve shift, such as my model illustrates, could hypothetically occur. I relay this information for contextual purposes only as the goal of my research is not to make predictions about the exact magnitude of the RES-E merit order effect, but rather to begin a preliminary discussion of how the market will react to increases in RES-E if demand side flexibility is induced through RTP. Therefore, this first scenario serves as a reference case and illustrates how wholesale prices would react if the expected increase occurred without any changes to the demand side of the market.

To simulate the second scenario (M2), the supply curve structure remains the same as the base case. Using five different demand elasticities that have previously been used in other studies analyzing the market impact of dynamic pricing, $\epsilon = \{-0.05, -0.03, -0.01, -0.1, -0.3\}$, I derive five separate demand curves, each representing different levels of price response through the variation in the five common elasticity estimates. For each level of price elasticity, I find the new equilibrium price and quantity, $(L_{RTP,\epsilon}^*, P_{RTP,\epsilon}^*)$ for each hour.

The final scenario applies both market changes (M1) and (M2) to the demand curve and supply curve using the methodology described in the previous scenarios. This scenario results in shifts of both curves. Again, I determine the new market clearing prices and volumes taking into account the shifts in both curves.

I repeat this process for each of the 4 hour types that this study analyzes.

5 Results

The following sections describe the results of the actual analysis following the methodology laid out in the model section. First, I contextualize the existing market by describing current conditions. In the next section, I introduce the hours that I use for the analysis given the set of criteria I previously described. The final sections address the results derived from the model and offer a comparative study of the price changes that occur from the different market scenarios, as well as the relative differences occurring amongst the set of 4 hours.

5.1 Analysis of Existing Market Conditions

Before studying the effect of my theoretical market changes on price (and traded volume), I explore the behavior of existing market characteristics that will impact my analysis; namely the load profile, distribution of prices and wind capacity. Furthermore, I explore the relationships between them. Understanding these relationships provides a solid foundation to contextualize the market changes which my analysis evaluates.

5.1.1 German Load Profile

Turning first to the behavior of the German power load; as expected, the daily and weekly load profiles of Germany follow widely observed peak and trough behavior. In terms of the daily load profile, peak hours occur in the afternoon and early evening and the hours of lowest demand occur during the middle of the night consistent with diurnal living patterns. On average, in 2009, the lowest demand occurred around 3 AM on weekdays, and, slightly later, at 5 AM on weekends. Average peak demand throughout the year occurred at 12 PM on both weekdays and weekends with a second spike around 7 PM. Weekly trend behavior follows the business week cycle, with days of highest demand occurring during the work week and low demand occurring on the weekend when large commercial and industrial users aren't consuming electricity. On average, weekend demand was about 10,000 MW lower than weekday demand, with yearly averages of 45,108 MW and 55,419 MW, respectively.

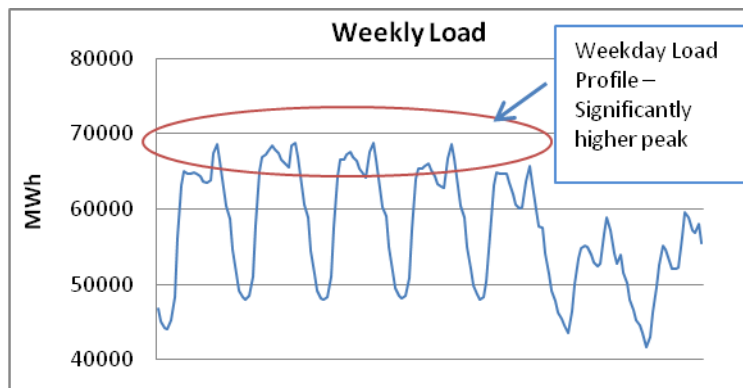


Figure 5: Weekly Load Profile - Germany, January 26 - February 1

The yearly load profile differs somewhat from that of the United States, due in part to significantly lower air-conditioning usage in Germany relative to the United States. (ECEEE, 2007). While in the United States, electricity consumption is highest during the summer months (EIA), German load is largest during the winter months with the highest demand occurring in the month of January for a total monthly consumption of over 42 TWh and the lowest occurring in April with a total consumption of 37 TWh (EEX).

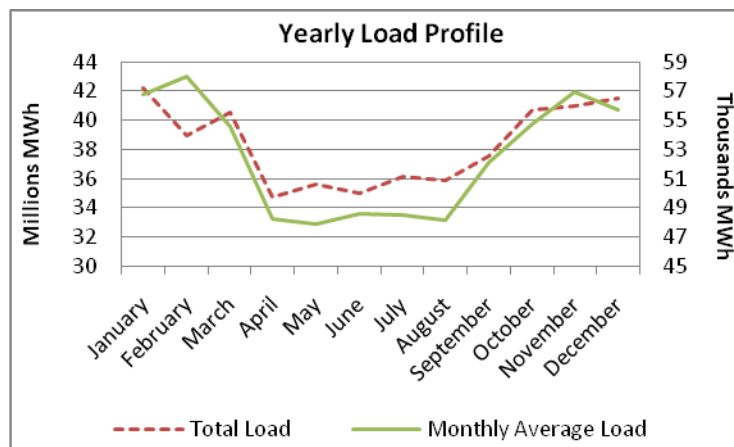


Figure 6: Germany's 2009 Total and Monthly Average Load

5.1.2 Price Behavior

In a market characterized by baseload generation with price stable inputs such as coal and nuclear, wholesale price behavior is almost entirely correlated with changes in wholesale demand. Even inter-hour changes in supply are due to expectations about future demand. Times of low demand are necessarily times when prices are low, due to the mandatory condition that supply and demand of electricity be kept in real time equilibrium. In this situation, variation in the price of baseload generation has little to do with cost and availability of the fuel inputs. As a caveat, this behavior is not withstanding the price volatility that is due to volatility in natural gas prices and price volatile fuel inputs that are used for peaking generators. This is just to say that when considering price volatility in baseload generation, little of the difference is due directly to the cost of fuel inputs like coal. However, in a market that has considerable amounts of baseload generation capacity from intermittent renewables, this is not necessarily the case.

The relationship between wind and power prices is complex and nuanced; but particularly for periods when wind infeed is high, there is evidence of a negative correlation between prices and wind generation (Nicolosi, 2010). In fact, amongst the 80 hours in 2009 when wind accounted for greater than 30% of the total electricity generated in Germany, there were only 3 hours when price exceeded the yearly wholesale average of €38.85/MWh. Furthermore, a large number of those hours cleared prices that were significantly lower than average, with 31 hours registering a price less than €1.00/MWh. Additionally, on days when significant negative prices occurred, the relationship is even stronger.

Using a simple linear regression to understand the relationship between wind and price, it can be seen that the correlation between the two variables is highest when wind generation is a significant portion of total generated load.

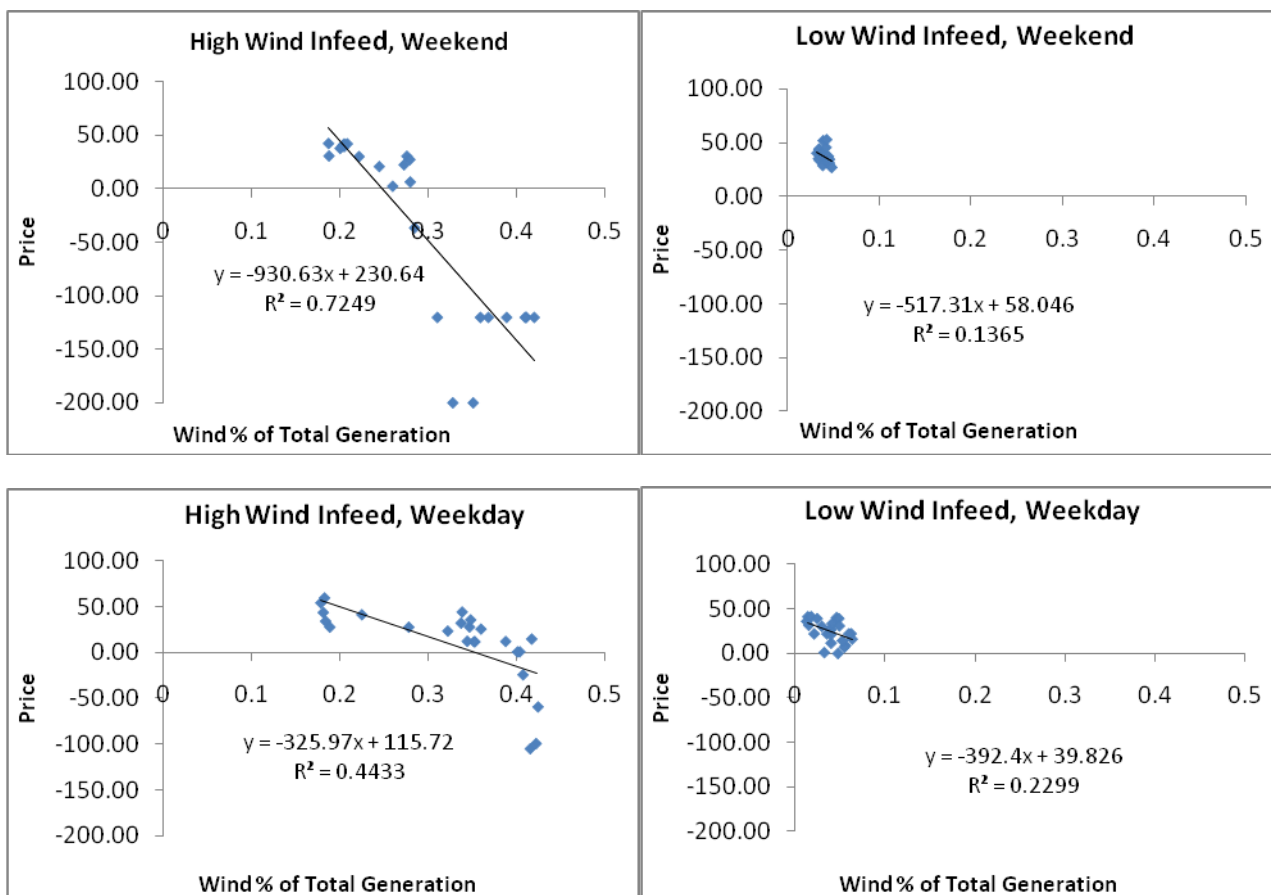


Figure 7

Comparing the level of volatility in prices across days with differing amounts of wind, we can see that on a day of low wind infeed prices tend to be more stable and clustered. Additionally, the amount of wind is not highly correlated with price, which we can see from the low R^2 value of graphs on the right of *Figure 7*.

In fact, on December 26, a weekend day with relatively high wind infeed over the course of the entire day, over 70% of variation in power prices is correlated with fluctuations in the wind percentage of total generation, an extraordinary amount considering all of the extraneous variables that have an effect on the supply and demand of electricity. When considering this high number, however, one should bear in mind that demand was also low over the course of the whole day since it was the day after Christmas. On a typical day with high wind infeed over the course of the entire day and negative prices, about 40% of price change is correlated with wind infeed variation, with the relationship between the two variables being statistically significant.

This suggests that as the amount of wind capacity increases, so too will the effects of wind infeed on prices, making this analysis – and others like it – increasingly important. Also, interestingly, by examining the correlation of wind infeed and prices during weekends versus weekdays, it can be shown that the correlation is higher on weekends than weekdays. Recalling that I previously showed that overall demand is on average higher on weekdays than weekends, it is reasonable to conclude that wind has the greatest effect on price during times when demand is relatively low. This suggests that RTP would be perfectly positioned to address the low prices by raising demand.

In order to understand the cumulative effects of an increase in wind infeed and the implementation of RTP on price, it is first important to understand the percentage of hours that would be most grossly affected by either or both market changes and also when those hours occur.

In 2009, only 1% of prices, or about 90 hours, fell below €0.00 per MWh. However, nearly 10% of prices, or about 900 hours, were below €20.00 per MWh, meaning that if wind capacity in Germany grows as projected by the BMU (BMU, 2009), significantly more hours could be in danger of falling close to zero or even negative.

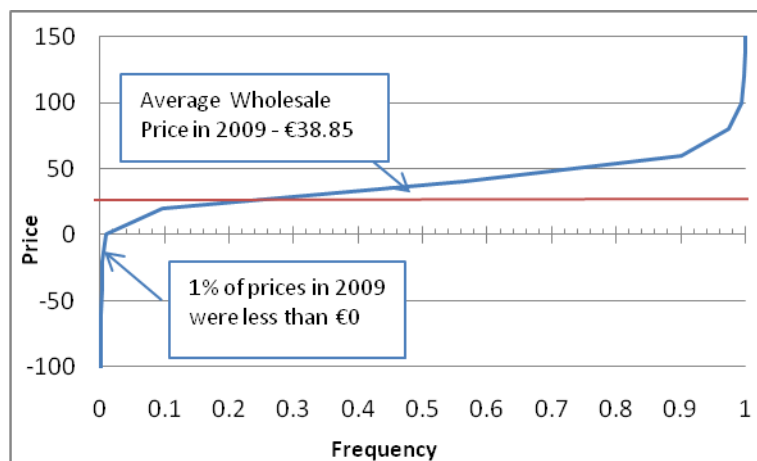


Figure 8: Price Distribution - Germany 2009

Of the 1% of prices that were negative, 50% of those hours occurred during the early morning hours of 5AM to 9AM. Furthermore, 62% of these hours occurred during the weekend.

Occurrence of Negative Prices	Weekday	Weekend	Grand Total
Early Morning	14.08%	36.62%	50.70%
Mid Day	2.82%	1.41%	4.23%
Night	21.13%	23.94%	45.07%
Grand Total	38.03%	61.97%	100.00%

Table 1: Table listing percentages of day and time negative prices occur

This occurrence seems consistent with expected price behavior because these are times when demand is low. We can therefore most likely expect negative prices during off-peak hours such as the weekend and early morning.

It has already been shown that the effects of RTP are significant in lowering volume and price during hours of extreme high prices even when only a small percentage of hours are directly affected (Borenstein, 2005; Spees, 2008; Braithwait and Sheasy, 2002; Patrick and Wolak, 1997). Therefore, even though prices significantly below average account for only a small portion of total hours, RTP may make a discernible difference on overall price behavior through changes to prices at the low margin.

5.1.3 Wind Behavior

There are two issues surrounding wind that create volatility in prices. The first issue is the inability to forecast wind. Without reliable forecasts, discrepancies between supply and demand can cause erratic price behavior. Both over- and under-prediction of wind infeed will result in poor estimates of available supply, which in turn will prevent other generation types from accurately scheduling their resources. The second issue is the nature of wind as an inherently intermittent phenomenon. Even if forecasting methods improve, wind will remain an erratic power source, meaning that without significant demand side management mechanisms in place, there is a large need for peaking generation. Regardless of advances in prediction methods, baseload generation, such as coal and nuclear, will be unable to react quickly to erratic wind changes and will choose to remain online and bid negative prices into the market.

When comparing monthly averages, total load and wind infeed follow similar patterns. This is due mostly to planning by the wind generators based on forecasts of expected demand.

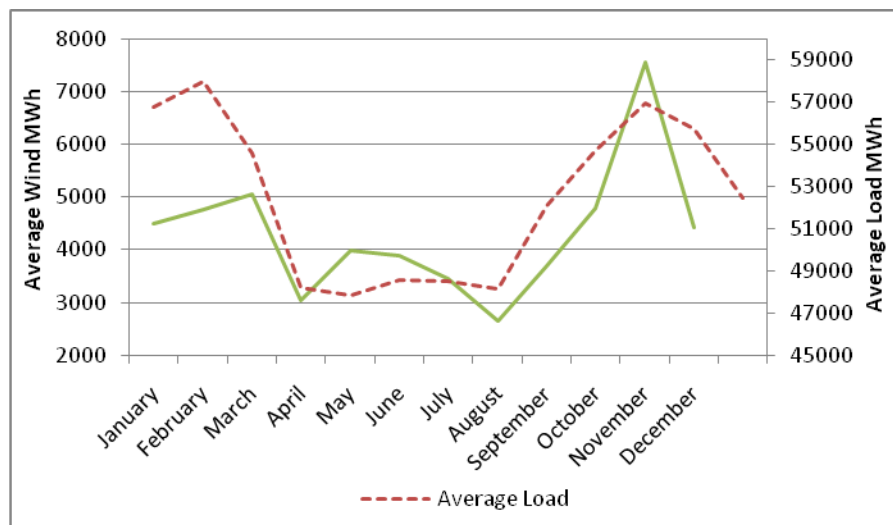


Figure 9: Comparison of the average hourly wind infeed and the average hourly load by month

Considering the relationship at a more granular level, however, reveals the disparity between the two variables. The graph below shows the lack of coincidence between the wind infeed and load.

As can be seen from *Figure 10*, total load during the 12 AM hour over the month of January follows the typical cyclical pattern with highest load during the week and low demand during the weekend. Comparing wind infeed for the same period during the same hour, one can immediately see the lack of relation between the two and the erratic stochastic behavior of the wind.

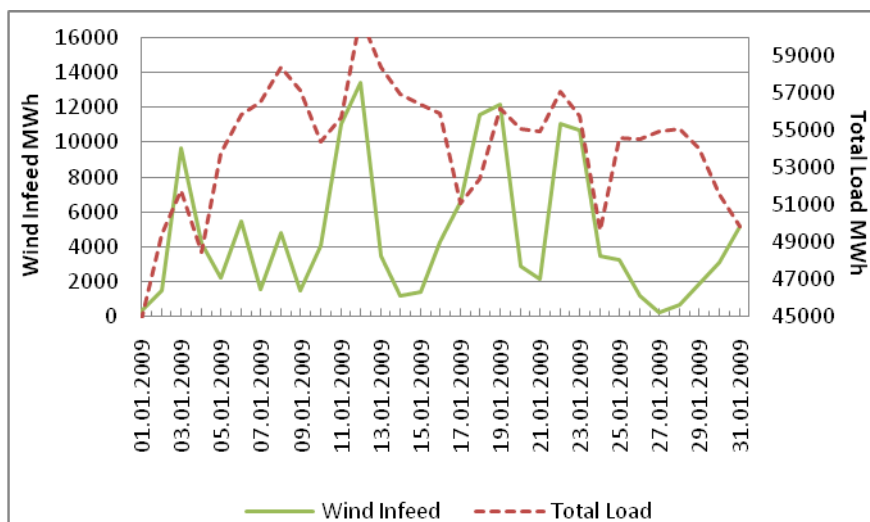


Figure 10: Comparison of the daily variation of wind and total load at 12 AM across the month of January

On average, wind MW accounted for only 8% of the total MW generated during each hour in 2009. The highest percentage of wind penetration was 42%, occurring on October 4th at 5 AM and the lowest percentage was 0.1% on June 29 at 11 AM. However, doubling capacity would have a drastic impact on those percentages. For this reason, I include an increase in wind generation as one of my market changes. Due to its relatively small percentage of total load on average in 2009, the analysis of the impacts of RTP might not be as informative as would an analysis of a market where wind makes up a greater portion of the generation portfolio.

5.2 Selection of Hours for Analysis

From the predetermined time period of January 1st 2009 to December 31st 2009, I pick a random sample of representative hours which I will use to compare the set of market changes described in the model specification section. As previously stated, the hours represent the following combinations of market characteristics: high demand, high wind infeed; high demand, low wind infeed; low demand, high wind infeed; low demand, low wind infeed. The distinctions for the different market conditions were given by the results from Genoese's study which analyzed the necessary market conditions for negative prices. Recalling that he states that negative prices occurred either when wind infeed was high (>12 GW) coupled with moderate system demand (40-50 GW) or moderate wind infeed (5-10 GW) coupled with low demand (<40 GW), I use these limits as the guidelines for my hour selection. For my analysis, I chose the set of two hours with low demand to have prices as close to zero as possible given the level of wind infeed needed for that particular representative hour – one hour with high wind infeed and one with low wind infeed. I chose these hours in order to examine what happens to price when the amount of wind generation increases and the current wholesale price is already approaching zero, to determine whether dynamic pricing will be able to mitigate any negative prices that occur due to the increased wind generation.

The hours I chose for the analysis are described in *Table 2*, including the date and time, the total electricity demanded in that hour and the amount of system-wide wind infeed.

	High Wind Infeed	Low Wind Infeed
High Demand	Jan 12 - 7 PM - Weekday Wind MW: 12594.75 Total Demand: 72826	Oct 7 - 8 PM - Weekday Wind MW: 2361.5 Total Demand: 65847
Low Demand	Mar 8 - 9 AM - Weekend Wind MW: 9914.25 Total Demand 43358	May 17 - 5 AM - Weekend Wind MW: 2276 Total Demand: 33394

Table 2: Matrix of hours selected for analysis

5.3 Analysis of Price Response to Market Changes

I first analyze how wholesale prices change when the amount of wind infeed increases, holding constant retail consumer behavior. I then apply the model specifications that simulate different levels of consumer price response for each hour, thereby producing a series of five demand curves. The following sections describe the results from applying the model to all four hours and then discuss the differences in price response that arise under varied market conditions.

My interest in this analysis is primarily in hours when wind infeed is high and demand is low, since this is when the majority of below average prices occur. I previously demonstrated that price and wind infeed have the highest level of correlation in these hours. Therefore, prices during these hours can be expected to exhibit lower prices and thus would benefit most from RTP. This is because, at these extremes, the elasticity of the merit order curve is lowest. In all hours, supply is elastic when price and volume are moderate and near the average. However, as the volume of load supplied approaches the margins in both directions, supply becomes less elastic, a phenomenon that can be attributed to high marginal cost of peaking generators at the high supply margin and the exorbitant shutdown and startup costs of coal and nuclear baseload generators at the low margin. Traditional studies of RTP have been concerned with understanding and manipulating the behavior of prices when demand is particularly high. These studies suggest that RTP can be used as a technique to drive price and volume demanded downward, closer to the average. However, adding intermittent renewables increases the need for balancing at both ends of the price extreme spectrum. Renewables can be beneficial at the high margins as they increase the volume of MW available at each respective price due to the merit order shift behavior of the supply curve with increased renewable penetration. However, this shift also affects the lower margin – increasing the volume of MW available at significantly low prices. The shift is not a concern during hours when demand is high; but, during hours of low demand, i.e. off-peak, early morning and weekend hours, there is a higher likelihood of low to negative prices. I, therefore, focus on hours in which demand is low and wind infeed is high because my analysis seeks to illustrate how RTP affects retail prices when wholesale prices close to or below €0.00.

5.3.1 Wholesale Price Change from Increased Wind Generation

Using the data compiled and the procedure outlined in the model specification section, the first step of the analysis plots the supply and demand curves under the existing market conditions to define the current market equilibrium conditions. The graphs in *Figure 11* illustrate the base case market equilibrium for each chosen hour, where the solid upward sloping line represents the supply curve with the existing generation mix.

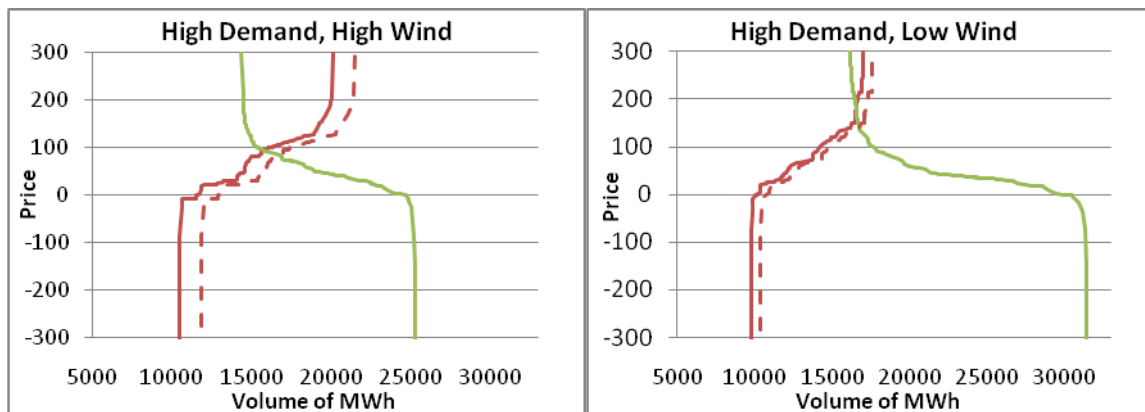


Figure 11a: Wholesale market with supply curves for existing and increased wind generation

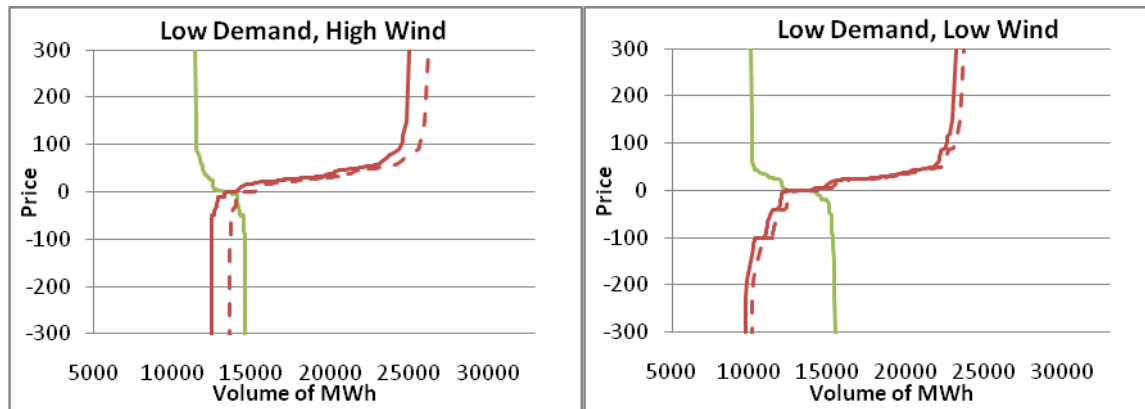


Figure 11b: Wholesale market with supply curves for existing and increased wind generation

I subsequently solve for the existing market clearing price and volume using these curves. Then for each of the hours, I increase the level of wind generation consistent with the procedure previously described based on the BMU's projection that Germany will double its wind capacity by 2025. In *Figure 11a* / *Figure 11b*, the dashed curve represents the new supply curve given the merit order shift that results from increasing the amount of wind generation. Again, I solve for the new market clearing price and column for each of the hours.

New Wholesale Prices			Existing Price	New Price	Δ Price
12-Jan	High Demand	High Wind	94.72	81.5	13.22
7-Oct		Low Wind	182.05	140	42.05
8-Mar	Low Demand	High Wind	0.02	-10.89	10.91
17-May		Low Wind	0.08	0.01	0.07

New Wholesale Volumes			Existing Volume	New Volume	Δ Volume
12-Jan	High Demand	High Wind	15739.9	16845	1105.1
7-Oct		Low Wind	16551	16768	217
8-Mar	Low Demand	High Wind	13709.7	14154	444.3
17-May		Low Wind	13537	13741	204

Table 3: Market clearing wholesale prices and volumes for current market conditions and an influx of wind generation

Table 3 lists the market clearing prices and volumes for both the existing supply curve and the new case with increased wind generation. For all hours, the table shows that wholesale price decreases and volume consumed increases when the amount of wind generation increases. The hour with lowest wind generation and greatest demand naturally has the highest prices, as is consistent with the analysis of price behavior performed earlier in the paper. Also, as predicted, the hour in which this price change is most problematic is the hour with low demand and high wind infeed. In this hour, prices drop below zero with a market clearing price of €-10.89.

The next step of the analysis will determine whether RTP can be utilized to raise price above zero in the case of the hour with negative prices and how effective dynamic pricing will be across all the representative hours.

5.2.3 Analysis of RTP

I first determined the average German retail price for 2009, using consumption and revenue data from the 4 largest German utilities. On average, I find the price per MWh to be 12.33, across all segments of electricity users. I construct my

linear demand curves around that point and the respective volume consumed for each hour as described in the model specification section.

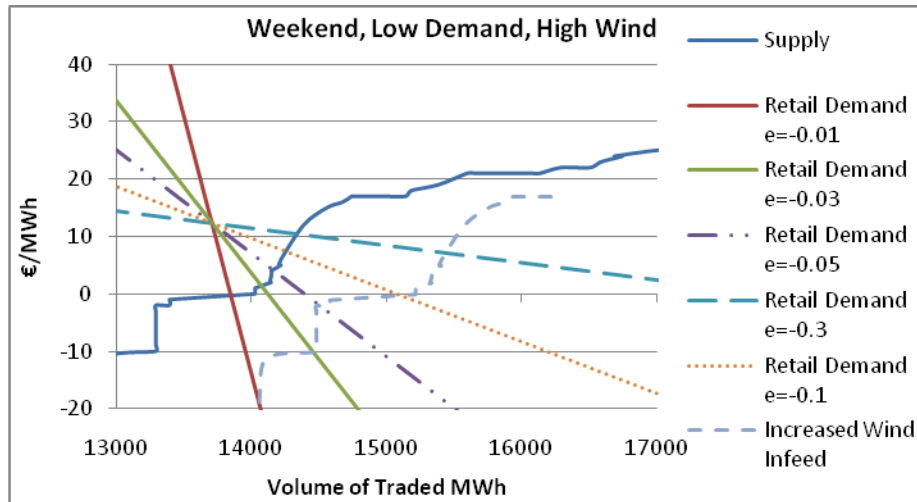


Figure 12: Model for Low Demand, High Wind Weekend hour

The graph in *Figure 12* represents the high wind, low demand hour with prices approaching zero.¹ The figure contains all of the linear demand curves with differing price elasticities and the two supply curves, one representing the existing wind penetration and the other the hypothetical increase.

After constructing the model for each hour, I use the resulting equilibria to give a relative scale for the price change resulting from inducing RTP, both with the existing and increased level of wind infeed, by plotting the resulting price against its given price elasticity. *Figure 13* illustrates the expected price for each level of price elasticity for hour of high demand and *Figure 14* does the same for the hours of low demand.

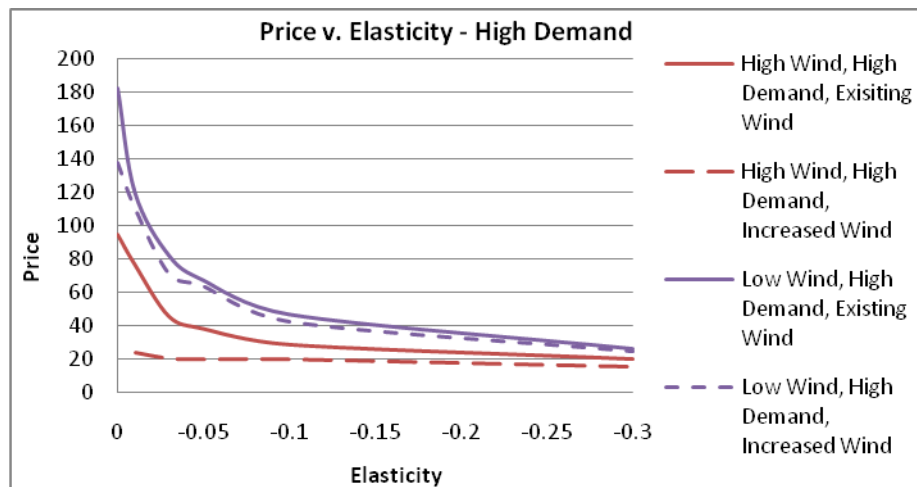


Figure 13: High Demand Hours - Market clearing price for different price elasticities

As other studies have shown, when the wholesale price is above the existing flat rate retail price, prices and consumption fall. The high demand, low wind infeed hour had the highest wholesale price under both the existing and increased levels of wind generation and therefore also exhibits that greatest response to RTP.

¹ Corresponding model figures for all hours can be found in the appendix.

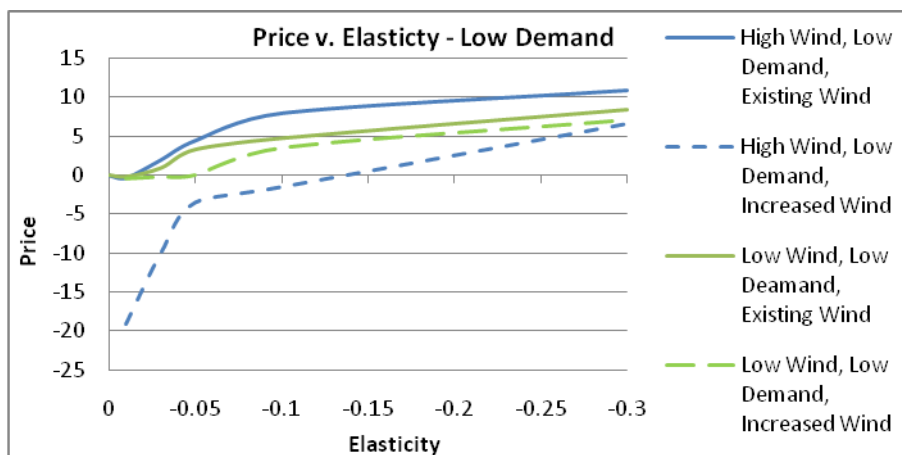


Figure 14: Low Demand Hours - Market clearing price for different price elasticities

Analyzing the effect of RTP on hours of low demand, we see the opposite behavior, as expected. In this case, prices rise because the wholesale price is significantly lower than the retail price consumers are currently facing.

I next turned my attention specifically to the hour with low demand and high wind infeed, as this is the hour in which the increase in wind generation resulted in a significantly negative price. In order to evaluate further whether RTP is a useful tool for mitigating such prices, after determining the expected clearing price for each level of elasticity, I was able to solve for the elasticity that would be needed during this hour to have the price reach at least zero by fitting a line through the calculated points. I determined that for the hour of low demand and high wind infeed, a price elasticity of at least -0.14 was needed to have a market clearing price of €0.00. Following the same logic, a price elasticity of approximately -0.44 was necessary to raise the price to be equal to the existing retail flat rate price. As this is outside of the short-run range of elasticity estimates given by previous studies, it seems unlikely that dynamic pricing would be able to raise prices high enough to equal the current flat rate retail price for this hour. Since the flat rate price, is not the efficient market price, however, I also evaluated how the new prices at each level of elasticity compare to the wholesale market clearing price with current flat rate retail price structure.

I find that, assuming consumers are almost completely averse to changing their consumption patterns regardless of exposure to price volatility, i.e. their price elasticity is essentially zero, RTP may not have a significant effect and in some cases might even be a hindrance to the market.

			New Wholesale Price	Elasticity Necessary for Retail Price to Match Existing Wholesale Price
12-Jan	High Demand	High Wind	81.5	0
7-Oct		Low Wind	140	0
8-Mar	Low Demand	High Wind	-10.89	-0.028
17-May		Low Wind	0.01	-0.051

Table 4: Elasticity necessary for RTP to impact wholesale price for each hour given an increase in wind generation

In the case of hours of high demand, even if consumers were highly averse to changing their consumption patterns, RTP would still drive prices down since if demand were perfectly inelastic the retail price under dynamic pricing would still be lower than the existing wholesale price. The effect, however, in reducing price volatility would be minimal as the wholesale price and volume under an RTP scheme would be barely lower than the price without consumer exposure to extreme prices.

Turning to the hours of low demand, there is a different story. In these hours, low levels of consumer price elasticity could potentially drive prices even lower than the wholesale price would be without dynamic pricing. Meaning that if consumers weren't responsive enough to fluctuations in price, a market with RTP could actually cause prices to be even *lower* than one without it. For instance, in the case of the hour of low demand and high wind infeed, a price elasticity of demand of at least -0.028 is needed for the price under RTP to be at least as high as the wholesale price without it. Such an occurrence makes a case for using full control demand side management techniques to ensure with greater certainty that an increase in electricity consumption occurs.

The preliminary results of this work are varied in terms of the impact that RTP has on raising low prices. Such results add further validity to my claim that exploring demand side management techniques to mitigate volatility caused by intermittent renewables is vital as generation portfolio expand their renewable penetration.

6 Preliminary Conclusions and Suggestions for Further Research

This analysis has shown that theoretically dynamic pricing could be used to correct the market inefficiency that results from negative prices, given the appropriate level of demand side price elasticity. However, from a practical policy stance, the likelihood of stimulating the necessary price response needed to organically create the load shift necessary is small. Since the majority of hours in which negative prices occur are late night or early morning, price elasticity can be expected to be fairly low. A policy maker would need to be careful to ensure that consumers could be induced to change their consumption patterns before implementing such a program. Having a good estimate for expected consumer price elasticity is critical for implementing an RTP plan to mitigate negative prices, since it can be shown that at very low levels of elasticity, RTP may even aid in further lowering negative prices.

Unfortunately, one of the confounding factors of this analysis was the disparate range of price elasticities that have been estimated for consumer behavior. My suggestion for further research into the subject would involve using survey results about consumer's preferences to estimate a demand curve for negative prices and then would compare the price response for an hour with a similar absolute value wholesale price. Also, I would suggest that the same analysis I preformed be applied to a larger set of data to determine how often this type of behavior holds.

In terms of implementing dynamic pricing mechanisms as a solution to reducing the occurrence and severity of negative prices, dynamic prices should be used in conjunction with other demand side management techniques. These techniques including full control demand response and storage techniques such as compressed air and pumped water can be coupled with more transparent retail pricing mechanisms, like RTP, to reduce the price volatility inherent in markets with significant intermittent renewable generation capacity. Full control demand response may create the artificial load increases (and drops) that would mimic the price elasticity induced by dynamic pricing. Because it is likely that any demand side response would have to occur during hours when few individuals could be enticed to change their consumption patterns and commercial and industrial facilities are not fully operational, full control automation is crucial. Furthermore, continued development of advanced metering and building management systems that include automatic start up and shut down controls activated at preset price floors and ceilings could make it easier for consumers to be responsive to dynamic prices during off peak hours. The proliferation of better battery systems, electric cars, and smart appliances could all increase the price elasticity of the average consumer and thus make dynamic pricing more attractive. Intelligent strategies combining these mechanisms could be used the reduce the negative externalities that traditional baseload generators incur by bidding negative prices into the system when wind generation is high without having to reduce the amount of generation that comes from renewables like wind.

This analysis is a preliminary attempt at understanding the benefits of using dynamic pricing to reduce price volatility. It should be used to facilitate more rigorous study of the topic, as intermittent renewable become more widely integrated into the grid. As more and more countries make commitments to improving energy security and limiting their carbon footprint, understanding methods that will allow markets utilizing renewables to function efficiently is vital. Dynamic pricing and, by extension, other demand side management solutions offering more comprehensive control may offer one such solution; but before they can be applied great care need be taken in analyzing its effects on a market-by-market basis.

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8 Appendix

Low Demand

		Elasticity	0	-0.01	-0.03	-0.05	-0.1	-0.3	
8-Mar	High Wind	Existing Wind	Volume	13709.7	13849.2	14054.28	14145.55	14207.09	14214.81
		Price	0.02	-0.27	2	4.45	7.91	10.81	
	Increased Wind	Volume	13709.7	14058.74	14456.15	14577.55	15212.5	15933.14	
		Price	-150	-19.11	-10.07	-3.5	-1.5	6.62	
17-May	Low Wind	Existing Wind	Volume	13537	13674	13911	14028.8	14365.07	14823.95
		Price	0.08	-0.1	0.99	3.33	4.76	8.37	
	Increased Wind	Volume	13537	13678.33	13952.12	14213.03	14510.04	15229.91	
		Price	-0.61	-0.49	-0.26	-0.03	3.49	7.13	

High Demand

		Elasticity	0	-0.01	-0.03	-0.05	-0.1	-0.3	
12-Jan	High Wind	Existing Wind	Volume	15739.9	14916.94	14462.57	14073.72	13611.97	12667.87
		Price	94.72	76.8	45.68	38.44	29	20.35	
	Increased Wind	Volume	15739.9	15589.16	15426.1	15250.44	14760.88	14554.64	
		Price	45.33	24.14	20.53	20	20	15.42	
7-Oct	Low Wind	Existing Wind	Volume	16551	15108.49	13753.6	12872.04	11999.96	10974.73
		Price	182.05	119.79	81.8	67.14	46.73	26.18	
	Increased Wind	Volume	16551	15227.14	14172.34	13076.42	12447.38	11394.09	
		Price	137.94	110.95	71.39	64.1	42.9	25.14	

Table 5: Market clearing price and volumes for a given elasticity across all hours

