Electricity Market Price Volatility: The Importance of Ramping Costs

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Abstract

Although electricity market price behavior generally has been well studied in the last decade, the literature is sparse when discussing the importance of generator ramping costs to price volatility. This paper contributes to the literature by first formalizing the intuitive link between ramping costs and price volatility in a multi-period competitive equilibrium. The fundamental result of the model shows how price volatility rises with ramping costs. This notion is tested empirically using a pooled event study regression, a two-stage least squares (2SLS) specification, and a generalized autoregressive conditional heteroskedasticity (GARCH) model. The econometric results all confirm that price volatility is significantly decreased by additional natural gas capacity, which has comparatively low ramping costs. This marks the first rigorous study to quantify the pecuniary externalities within the New England market's generating profile, showing over a million dollars worth of price stability provided per year by each new natural gas generator. A simulation also explores how this value changes over time, noting that value of price stability from natural gas generators will increase with the proportion of non-dispatchable renewable generators.

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1 Introduction

Within the past fifteen years, most electricity markets across the United States have restructured to allow competition in the generation of electricity. Electricity price behavior has been extensively studied as it relates to market design (Wolak and Patrick, 2001, Borenstein et al., 2002, Chang and Park, 2007, Metaxoglou and Smith, 2007, Bushnell et al., 2008, Bask and Widerberg, 2009) and price volatility generally (Hadsell et al., 2004, Worthington et al., 2005, Zareipour et al., 2007, Higgs and Worthington, 2008, Higgs, 2009). However, there are fewer studies which examine how price volatility is influenced by the generating profile of the market. This is important because high volatility has plagued wholesale electricity prices since restructuring, creating major implications for risk-averse market participants and system operators tasked with grid reliability. Further, price volatility is a primary input into conventional options pricing models, pushing real costs onto consumers of electricity as power purchasing retailers use costly options to hedge away from price risk. When compared to other energy commodities, intra-day volatility in wholesale electricity markets is many times larger and varies across regions. For example, daily electricity market volatility ranges from 6-28% compared to 1-1.5%, 2-3%, and 3-5% for stock indices, crude oil, and natural gas, respectively (Simonsen, 2005, Zareipour et al., 2007).

With the rise of non-dispatchable renewable generators such as wind and solar, short run volatility has grown increasingly important to Regional Transmission Organizations (RTO) managing the electricity grid (Navid and Rosenwald, 2012). To ensure adequate ability of adjusting generator output, known as ramping ability, grid operators are discussing alterations to the current market design in California (Xu and Tretheway, 2012) and the Midwest (Navid and Rosenwald, 2013). Under the standard market design, ramping ability will be properly priced in a deterministic model because flexible generators that can quickly adjust output will be able to profit from large movements in price. However, in reality actual market conditions often deviate from those previously scheduled by the RTO. It has been shown that the current market design may not properly price short-term ramping ability due to suboptimal dispatching under uncertainty (Angelidi, 2012, Wang and Hobbs, 2014). When designing an electricity market for the generating profile of the future, it is important to thoroughly understand how different generator types affect price volatility. The increased investment in natural gas generators over the last decade and the anticipated rise of renewables helps to motivate the focus of this paper, since the direct effect of natural gas capacity on electricity price volatility has not been well studied.

Much of variability in electricity prices is driven by the physical characteristics of electricity, notably the requirement to perfectly adjust supply to meet a demand that varies significantly throughout the day and across seasons. The mainstream view is that high price volatility within electricity markets is due to the lack of hourly retail pricing in combination with the lack of cost-effective electricity storage mechanisms. In traditional commodity markets, forward contracts stabilize spot prices because any deviations allow for arbitrage through selling previously stored goods (Kaldor, 1939, Working, 1948). However, current technologies do not allow cost-effective electricity storage on any meaningful scale, rendering traditional forward pricing models inapplicable. Instead, Bessembinder and Lemmon (2002) develop a seminal equilibrium model of forward contracts between risk-averse electricity generators and retailers, which implies a forward contract premium to accompany high expected demand or demand variance. The essentials of their model are empirically supported (Longstaff and Wang, 2004, Cartea and Villaplana, 2008, Douglas and Popova, 2008), though more recently Haugom and Ullrich (2012*b*) find that the forward price has converged to an unbiased predictor of the spot price.

While Bessembinder and Lemmon (2002) capture the essentials behind forward contracts in non-storable commodities, their model ignores the storability of inputs to electricity generation. Intuitively, if inputs can be stored and capacity exists to instantaneously convert these inputs into electricity, then a stabilizing pressure is applied to price during unexpected demand shocks. Further, there exists a cross-commodity price relationship as pointed out by Routledge et al. (2001) in an extension of their previous work (Routledge et al., 2000). This notion is empirically tested by Douglas and Popova (2008), who find that larger natural gas storage decreases the premium of forward contracts. While they note that the effectiveness of the indirect physical hedge requires availability of transmission and generation capacity, this is absent from their empirical specification. Further, natural gas storage is likely endogenous to electricity price and forward contract premiums, creating bias in their empirical estimates. In a separate analysis across European electricity markets, Huisman and Kilic (2012) attribute differences in risk premiums to be from differences in the storability implicit within the generation profile, a point more explicitly noted previously (Huisman and Kilic, 2010). However, cross-sectional analysis is inadequate to infer causal relationships when the markets also vary widely in both observable and unobservable characteristics. My empirical analysis improves on this literature by considering endogeneity issues associated with the supply of generator types and electricity price.

Intuitively, different generator technologies would affect volatility differently, as they vary in their ability to adjust output. Heterogeneity in ramping costs, or costs of adjusting output, allow some generators to flexibly adjust output during periods of higher demand, putting more downward pressure on prices compared to other generators (Reguant, 2014). In this paper, I seek to understand the role of ramping costs in the price volatility of non-storable and perishable commodities. More specifically, I ask three connected research questions related to natural gas capacity, which has comparatively low ramping costs (Wolak, 2007, Reguant, 2014). First, what is the impact of additional natural gas capacity on electricity price stability and how does this compare to inflexible capacity such as nuclear? Further, what is the value of such volatility reductions to power purchasers? Lastly, how does the forward premium change on price contracts in the presence of additional natural gas capacity?

To explore this topic, a basic theoretical framework is developed to establish the connection between price volatility and generator ramping costs. Under standard economic assumptions, the analytical model clearly suggests that price volatility increases with generator ramping costs. Further, the theoretical model implies a reduced form econometric specification where the intra-day price volatility is a function of natural gas capacity, intra-day demand volatility, daily average demand, and unobservable time trends. To explore these ideas empirically, I use high-frequency price data from the New England Independent Systems Operator for the period 2005-2011. Data on natural gas capacity and nuclear capacity outages are taken from the U.S. Energy Information Agency and the U.S. Nuclear Regulatory Commission, respectively. The task is complicated by endogeneity between price and capacity, since natural gas is the marginal generator in New England, but these issues are considered.

The preferred results include a pooled event study regression, which finds strong evidence that natural gas capacity additions reduce price volatility an order of magnitude more than additional nuclear generation capacity. These results are robust to a two-stage least squares (2SLS) specification, as well as a generalized autoregressive conditional heteroskedasticity (GARCH) model. I attribute the differences in volatility reductions between the two generator types to the relatively low ramping costs of natural gas. This translates to an increase in consumer surplus by over a million dollars per generator per year, although this is not interpreted as a reduction in the deadweight loss. Lastly, a simulation explores how the price stability value of natural gas generators changes over time, showing that it increases with the proportion of non-dispatchable renewable generation, such as wind power. In terms of volatility impact, natural gas provides an excellent compliment to new wind generation in the New England market.

This research adds to the broad existing literature that discusses electricity market design (Wolak and Patrick, 2001, Navid and Rosenwald, 2012, Wang and Hobbs, 2014, Reguant, 2014), market efficiency (Borenstein et al., 2002, Metaxoglou and Smith, 2007), electricity price behavior (Hadsell et al., 2004, Worthington et al., 2005), and forward premiums on perishable commodities (Bessembinder and Lemmon, 2002, Longstaff and Wang, 2004, Douglas and Popova, 2008, Haugom and Ullrich, 2012*b*). By formalizing the link between ramping costs and price volatility, the model provides a clear theoretical mechanism to explain how ramping costs increase price volatility. Most importantly, this research provides the first rigorous empirical analysis that supports the role of natural gas capacity to reduce price volatility. This research provides concrete evidence for policymakers to consider the pecuniary externalities associated with generation types. This underscores the importance of investments into ramping ability, which adds to the current discussion on market design alterations. While environmental externalities are beyond the scope of this analysis, ramping costs are also important for such researchers to consider because they can fundamentally alter the abatement cost curves, as they may change the dispatch order of generators.

The remainder of this paper proceeds as follows. Section 2 gives a brief background of the New England electricity market structure while Section 2.1 discusses ramping costs in more detail. The theoretical framework is established in Section 3, which formalizes the intuitions described above into a basic analytical model. The econometric strategy to test these relationships is described in Section 4, while the related data are discussed in Section 5. The results are presented in Section 6, with the option pricing effects noted in Section 7. Finally, additional regression analysis studying the impact of natural gas capacity on the forward premium is provided in Section 8, while Section 9 concludes.

2 New England ISO Market Background

Prior to the 1990s, New England's electricity market was comprised of vertically integrated monopolies that were heavily regulated. Private and municipal utilities managed the region's electricity grid through the New England Power Pool (NEPOOL) created in the early 1970s. However, by 1996 the Federal Energy Regulatory Commission (FERC) issued orders that encouraged wholesale electricity markets for competitive electricity generation. The FERC created general guidelines with a recommended market structure where a non-profit Regional Transmission Organization (RTO) is entrusted to manage the transmission grid and electricity markets. This paved the way for the creation of the Independent Systems Operator of New England (ISO-NE) in 1997 to oversee the market restructuring, ensure grid reliability, and establish competitive markets. (ISO-NE, 2014*a*)

New England's competitive electricity markets were first implemented in 1999 and now cover 14 million people across six states.[1] The wholesale market includes over 500 participants and the ISO-NE coordinates over 8,000 miles of transmission lines (ISO-NE, 2014*c*). After restructuring, consumers can choose between several licensed utilities which are responsible for the retail delivery of electricity. Typically residential consumers pay a constant marginal cost for electricity at a rate fixed for several months and face no hourly price pressure from the wholesale market. Thus, consistent with the prior literature, the rest of this analysis assumes demand to be exogenous to wholesale prices at the hourly level.[2]

Major changes to the wholesale market occurred in 2003 when the ISO-NE adopted the "Standard Market Design" of FERC, which established locational marginal pricing,[3] financial transmission rights,[4] and a dual-settlement market. The dual-settlement market system provides a day-ahead market and a real-time market, which clear separately through two com-

[1] The New England market includes Maine, Vermont, New Hampshire, Massachusetts, Connecticut, and Rhode Island.

[2] At longer time horizons, changes in wholesale electricity prices are eventually passed on to the consumer but the exogeneity assumption is arguably most appropriate for the frequency of the data used in this analysis.

[3] Locational marginal pricing (LMP) is required for efficient markets because of transmission capacity constraints which impose congestion costs. For each node and load zone in the ISO-NE, supply and demand offers are submitted such that the LMP provides the competitive price inclusive of congestion costs. If congestion and transmission losses are zero, the efficient price is equivalent across all nodes and their zonal aggregates.

[4] Since LMP includes congestion costs paid to the ISO-NE by power purchasers, the suppliers may receive less revenue than the final price that includes congestion costs. Thus, financial transmission rights (FTR) are auctioned to market participants, giving them a share of the real-time congestion payments that are absent from the day-ahead market price. For power purchasers, this acts as a hedge against unexpected higher congestion costs, while it can also provide additional revenue for generators or speculators.

petitive auctions. (ISO-NE, 2014*b*)

In the day-ahead market, participants provide hourly bids for the supply and demand[5] of electricity that will be dispatched the following day. For each hour of scheduled delivery, the bids are due by noon of the prior day. ISO-NE then stacks the bids into hourly aggregate supply and demand curves and schedules electricity to be delivered for all bidders below the intersection of supply and demand. While the day-ahead market is purely financial since no electricity is physically delivered, suppliers must deliver the agreed amount of electricity in the corresponding hour of the following day. In the event of equipment malfunction, for example, the supplier cannot deliver the ex-ante scheduled amount of power and they are required to buy the appropriate amount in the real-time market. (ISO-NE, 2014*b*)

After the first round of commitment in the day-ahead market, ISO-NE performs a reliability assessment based on its own demand forecast and a "re-offer" period begins. Supply and demand that has not been previously scheduled is eligible for bidding in this market, which forms the foundation of the real-time market. Throughout the following trading day the ISO-NE physically balances supply and demand through these hourly bids while maintaining grid stability through a sufficient operating reserve of electricity. The real-time market prices are from ex-post settlements based on actual power delivery that may deviate from expected demand. (ISO-NE, 2014*b*)

Although the day-ahead market is purely financial, risk averse market participants may prefer the day-ahead schedule. The day-ahead pricing is typically more stable because it is based on expected outcomes, but real demand variations can be unexpected. To ensure the convergence of day-ahead prices with real-time prices, the ISO-NE also allows "virtual bids", which are purely financial trades in the day-ahead market that must be closed out in the real-time market. Thus, any consistent and profitable arbitrage opportunities between the two markets should be removed in the presence of virtual bidding by risk-neutral participants, leaving only a small risk premium. With risk averse participants, the forward premium should be significantly driven by the variance and skewness of spot market prices (Bessembinder and Lemmon, 2002), as previously discussed.

Overall, the New England market is primarily served by electricity generation from nuclear

[5]While demand is exogenously determined by retail customers, retail utilities have a choice to buy electricity in the day-ahead market or the real-time market. Any unscheduled electricity demanded in the day-ahead market is required to be purchased in the real-time market.

and natural gas. The total GWh generation by source is provided by the ISO-NE and shown in Table 1 for 2005-2011, the entire period studied in this analysis. In 2011, generation from nuclear and natural gas facilities comprised around 67% of total generation, not including the 13% from dual-fuel generators, much of which can be attributed to natural gas as well. Meanwhile, coal, hydro, and aggregate non-hydro renewables[6] each generate close to 6% of the ISO-NE total. Thus, this analysis focuses on the two largest generator types of nuclear and natural gas to understand the role of ramping costs in price volatility. Generally, natural gas generators are the marginal unit throughout most of the year, while new nuclear has been discussed as a hedge against the fossil-fuel price volatility that underlies electricity price risk (Roques et al., 2006, Kessides, 2010).

Table 1: New England Generation Profile: Annual GWh from 2005-2011

Source	2011	2010	2009	2008	2007	2006	2005
Total Generation	120,610	126,416	119,437	124,749	130,723	128,050	131,877
	100%	100%	100%	100%	100%	100%	100%
Gas	46,378	42,042	38,163	38,338	39,367	39,425	38,583
	38.45%	33.26%	31.95%	30.73%	30.11%	30.79%	29.26%
Nuclear	34,283	38,364	36,231	35,547	36,972	36,923	34,609
	28.42%	30.35%	30.33%	28.49%	28.28%	28.83%	26.24%
Oil/Gas†	15,925	15,542	12,487	12,721	15,791	13,542	16567
	13.2%	12.29%	10.45%	10.2%	12.08%	10.58%	12.56%
Hydro	8,252	7,227	8,354	8,466	6,385	7,498	6,739
	6.84%	5.72%	6.99%	6.79%	4.88%	5.86%	5.11%
Renewables	7,261	7,686	7,331	7,539	7,818	7,675	7,599
	6.02%	6.08%	6.14%	6.04%	5.98%	5.99%	5.76%
Coal	7,080	14,131	14,558	18,596	19,770	19,375	20,789
	5.87%	11.18%	12.19%	14.91%	15.12%	15.13%	15.76%
Pumped Hydro	1,149	854	1,419	1,623	1,744	1,582	1,339
	0.95%	0.68%	1.19%	1.3%	1.33%	1.24%	1.02%
Oil	282	570	895	1,918	2,877	2,030	5,652
	0.23%	0.45%	0.75%	1.54%	2.2%	1.59%	4.29%

†ISO-NE does not have data splitting generation by fuel in dual-fuel units.

While the ISO-NE wholesale electricity market generally operates independently, there are also thirteen interconnections that allow for the purchase and sale of electricity to grids in New York and Canada. The annual flows of electricity from 2005-2011 are listed for the ISO-NE in Table 2. On average, net imports account for 5.7% of electricity consumed within the ISO-

[6] Within non-hydro renewable generation for 2011, 4.9% of total generation is from wood and refuse, 0.6% from wind, and less than 0.3% from landfill gas or solar.

Table 2: New England Electricity Flow: Annual GWh from 2005-2011

	2011	2010	2009	2008	2007	2006	2005
Total Demand	129,163	130,773	126,838	131,753	134,466	132,087	136,355
	100%	100%	100%	100%	100%	100%	100%
Total Generation	120,610	126,416	119,437	124,749	130,723	128,050	131,877
	93.38%	96.67%	94.16%	94.68%	97.22%	96.94%	96.72%
Pumped Hydro†	-1,589	-1,183	-1,963	-2,247	-2,403	-2,156	-1,819
	-1.23%	-0.9%	-1.55%	-1.71%	-1.79%	-1.63%	-1.33%
Imports	15,880	12,781	15,226	14,256	12,269	10,762	10,152
Exports	5,738	7,242	5,863	5,005	6,122	4,569	3,855
Net Imports	10,142	5,539	9,363	9,251	6,146	6,193	6,297
	7.85%	4.24%	7.38%	7.02%	4.57%	4.69%	4.62%

†Pumped hydro is a net loss of energy generation but can still occasionally be optimal. Essentially it provides relatively small indirect storage of electricity during low demand periods that is released during peak demand periods.

NE. The ISO-NE is a net exporter of electricity to the New York ISO, but a net importer from Quebec. From 2005 to 2011, demand has decreased by 5.3% while total generation has decreased by 8.5%. The difference is made up though additional imports which have generally increased over time.

2.1 Ramping Costs

Electricity generation is itself a complex process, made more complicated through the necessity of balancing supply and demand instantaneously to prevent grid failure. In typical fossil-fuel generators, fuel is burned to convert the embedded chemical energy into thermal energy which heats up water into steam. The pressurized steam flows to turn a turbine, which is connected to a generator that converts the mechanical energy into electricity. Nuclear reactors work in a similar way, except the nuclear reaction creates the heat for the steam turbine.

The mechanical complexity inherent to the generation process imposes extra costs to adjusting electrical output from hour to hour, known as ramping costs. Ramping costs appear through fixed investments as well as marginal costs. Within the fixed costs, physical ramping constraints accompany certain technologies and these require higher investments to overcome. For example, the turbine system and related components require special designs and construction materials to be able to rapidly ramp output and to withstand the extra stress of ramping without failure (Tanaka, 2006).

Regarding marginal costs, previous literature notes that ramping output up or down will decrease the fuel efficiency of the unit compared to a constant operating output. Further, ramping output puts additional stress on the generator components, leading to larger replacement costs. More specifically, ramping induces rapid pressurization and decompression which stresses essential pieces such as the rotor, turbine shaft blades, boiler, and turbine chamber (Tanaka, 2006). This thermal stress induces microscopic fractures known in the engineering literature as "fatigue damage", which is the second leading cause of boiler tube failure (EPRI, 2006).

Engineering studies also note that fatigue damage to the rotor assembly increases non-linearly with ramping speed and can alter the optimal commitment of generating units (Wang and Shahidehpour, 1994, 1995). Regarding the efficient dispatch of generators, Shrestha et al. (2004) note that ramping may be used strategically in deregulated markets. They point out that, in general, generators start up and shut down slowly to avoid any ramping costs and turbine damage. However, during periods of high prices it can be profitable to incur ramping costs if the generator has sufficient capacity. This is consistent with the intuition behind the theoretical and empirical approach in Sections 3 and 4, respectively.

There are also indirect costs associated with ramping ability. The lower ramping costs associated with natural gas generators presumably enhance grid stability and allow reliable grid operation with lower reserve margins. operating reserves to be sufficient. Additionally, if sufficient capacity does not exist with ramping capabilities to accompany demand changes then there is a large risk of system blackouts. These considerations are discussed by Chao (1983), as blackout risk imposes significant economic costs. However, my analysis is concerned primarily with price risk, so changes to the probability of grid failure due to ramping ability is left for future researchers.

Since the focus of this analysis is on natural gas capacity and nuclear capacity, it is worth noting their differences in ramping ability. The marginal operating costs of nuclear generators are estimated to be one fourth of natural gas generator marginal costs (EIA, 2013*a*) so they generally provide the base load of the electricity supply. Further, technical constraints make cost-effective hourly ramping of nuclear generators infeasible. Nuclear generators may take an entire day to start up or shut down during planned outages, although in emergency situations the reactor can shut down very quickly. Meanwhile, natural gas generators are considered more flexible and follow increases in demand throughout the day. This is confirmed by previous literature which finds that natural gas generators have ramping costs an order of magnitude lower than coal (Wolak, 2007, Reguant, 2014). Lastly, wind and solar generators are non-dispatchable technologies without ramping options, and they are ignored in this analysis because they represent an insignificant portion of supply in the ISO-NE. However, their growing presence increases the relevance of the issues studied here because their inherent supply intermittency increases the volatility of residual demand satisfied by dispatchable generators such as natural gas. This impact is explored using the simulation in Section 7.1.

3 Theoretical Model

Before discussing the empirical approach, this section formalizes the economic intuition into a basic dynamic model where firms generate electricity to maximize daily profits, π, in a competitive wholesale market. Each day a representative firm i chooses the optimal quantity of electricity, q, to produce in hour h, in order to maximize their profits. Assuming a competitive wholesale market, firms are given hourly market clearing electricity prices, p_h. The model uses a simple generalized cost structure similar to the previous literature (Wolak, 2007, Reguant, 2014), and assumes a convex production cost function, $C_i(q_h)$. There is also assumed to be convexities in the ramping cost function, $R_i(\Delta_{i,h})$ where the change in hourly production is denoted as $\Delta_{i,h} = |q_{i,h} - q_{i,h-1}|$. Demand, D, is exogenous because consumers face a regulated retail price that prevents hourly price pressure, as discussed in Section 2. Adding fixed costs, F, yields the following objective function for production firms:

$$\max_{q_{h,i}} \pi_i = \sum_{h=1}^{24} \delta_h [p_h q_{i,h} - C_i(q_{i,h}) - R_i(\Delta_{i,h})] - F_i \text{ subject to } \pi \geq 0, q_h \geq 0, D_h = \sum_{i}^{n} q_{i,h} \quad (1)$$

where δ_h is the hourly market discount factor and n is the number of firms. The first two constraints represent non-negative production and non-negative daily profits, though hourly profits can be negative. The final constraint is the standard market clearing condition where production equals demand. Solving for the first order conditions yields the standard result of price equal to marginal costs, for each firm i in hour h:

$$p_h = \frac{\partial C_i}{\partial q_{i,h}} + \frac{\partial R_i}{\partial \Delta_{i,h}} \frac{\partial \Delta_{i,h}}{\partial q_{i,h}} \tag{2}$$

Recall that the intra-day variance of p on day t, denoted by σ_t^p, is defined:

$$\sigma_t^p = \frac{1}{24} \sum_{h=1}^{24} (p_{t,h} - \bar{p}_t)^2 \tag{3}$$

where $\bar{p}_t$ is the daily average price. Substituting in equation (2) to equation (3) and simplifying yields the fundamental result of this model:

$$\sigma_t^p = \frac{1}{24} \sum_{h=1}^{24} \left(\frac{\partial C_i}{\partial q_{i,h}} + \frac{\partial R_i}{\partial \Delta_{i,h}} \frac{\partial \Delta_{i,h}}{\partial q_{i,h}} - \frac{\sum_{j=1}^{24} \left(\frac{\partial C_i}{\partial q_{i,j}} + \frac{\partial R_i}{\partial \Delta_{i,j}} \frac{\partial \Delta_{i,j}}{\partial q_{i,j}} \right)}{24} \right)^2 \tag{4}$$

As is clear from equation (4) above, price variance depends on the marginal costs of production, marginal costs of ramping, and the variance of demand. The intuition behind this result is straightforward, as the intra-day price variance will depend on the convexity of the supply curve and ramping costs. Decreasing the marginal costs will lower price variance because demand intersects a flatter portion of the convex supply curve. Since the point of convexity along the supply curve is dependent on demand, the model also implies a higher variance during periods of higher demand, *ceteris paribus*. Further, demand volatility is fundamentally driving the price volatility so the model suggests that price volatility increases with demand volatility.

To illustrate this point more clearly, consider a basic two period model where demand increases from D_1 to D_2 such that $\Delta = q_2 - q_1 > 0$ is the change in production. This is shown graphically on Figure 1. Without ramping costs the supply curve in both periods remains the same, shown as S, and the simple shift from D_1 to D_2 yields the prices equal to marginal production costs, $p_1 = \partial C_1$ and $p_2 = \partial C_2$ for periods 1 and 2, respectively. However, with ramping costs, the equilibrium prices now become $p_1 = \partial C_1 - \partial R$ and $p_2 = \partial C_2 + \partial R$ for periods 1 and 2, respectively. Intuitively, firms are willing to produce quantities above those at marginal production cost in period 1 in order to have lower ramping costs in period 2. This is

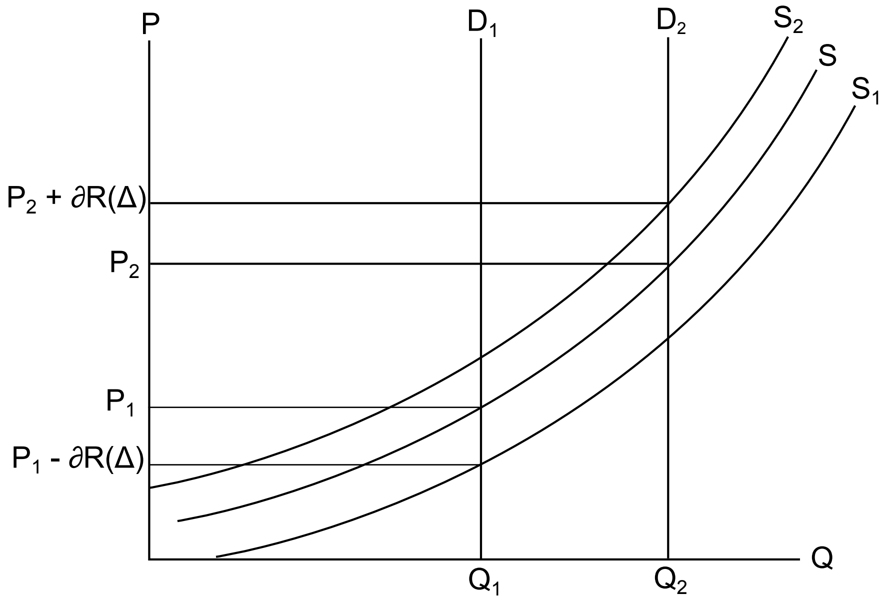

Figure 1: Supply and Demand Curves with Ramping Costs

shown on Figure 1 as a shift from S to S_1 causing a decrease in prices.

In period 2 firms produce quantities below marginal production costs because of ramping constraints. This shifts the supply curve to S_2 in Figure 1, increasing prices beyond the equilibrium level without ramping costs. Thus, any losses from "over-production" in period 1 are recouped through lower ramping costs in the profit maximizing multi-period equilibrium.

Adding new capacity with lower ramping costs has two effects. First, the supply curve shifts outward, which will decrease the difference between p_1 and p_2 because the respective demands now intersect a flatter part of the supply curve. Second, the lower ramping costs squeezes S_1 and S_2 closer to each other, which again decreases the price difference between periods. This is shown graphically in Figure 2, where the new equilibrium is shown in red, and the old equilibrium from Figure 1 is left in light gray for comparison. Thus, the variance in prices unambiguously decreases from adding new capacity with lower ramping costs and lower marginal production costs.

As discussed in the previous sections, natural gas occupies a critical point along the supply curve where it is the marginal generating unit. Thus, there are two effects from adding new natural gas capacity as captured by the model. First, adding additional new natural gas capacity will lower total marginal costs because the new technologies are assumed to be slightly more

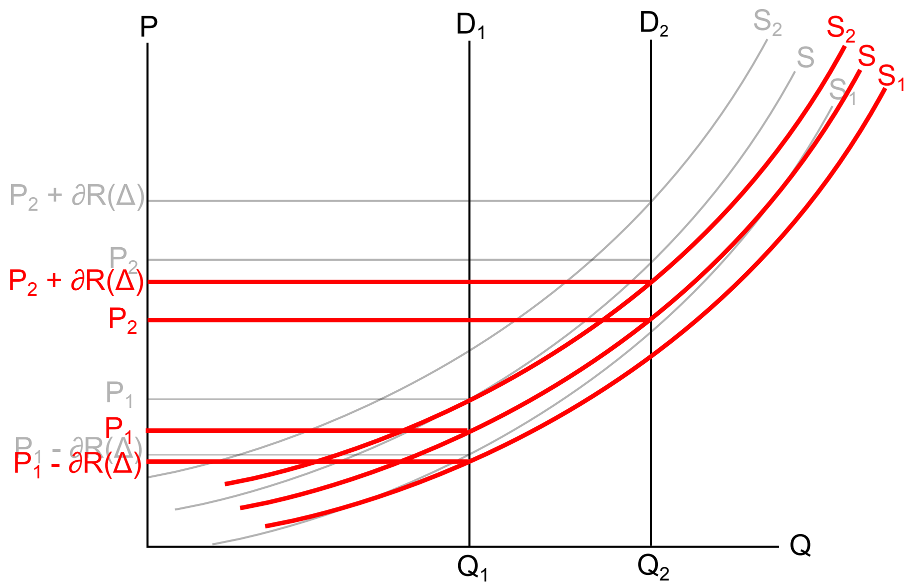

Figure 2: Shifting Supply with New Capacity

efficient than current marginal units. I define this as the "supply shift" effect on volatility. This assumption is validated empirically by the decreasing average heat-rate in natural gas units over the last decade (EIA, 2013*b*). The second effect from adding new natural gas capacity, as captured by the model, is decreasing ramping costs. I define the "ramping effect" as the resulting volatility reduction from a decrease in ramping cost associated with new natural gas capacity. Again, this assumption is justified by empirical analysis (Wolak, 2007, Reguant, 2014), as natural gas units have lower ramping costs than coal-fired power plants. Thus, adding natural gas capacity should unambiguously decrease price volatility, *ceteris paribus*.

Meanwhile, nuclear capacity additions should provide only the supply shift effect because it provides baseload power on the far left portion of the supply curve. As previously noted, nuclear technology has a very low marginal cost and generally operates throughout the day without ramping. Thus, the theoretical model implies that changes in active nuclear capacity should reduce price volatility, but less than the volatility reductions from natural gas. The difference between the volatility reductions from these two generator types is interpreted as the ramping effect. This fundamental result of the model is tested in Section 4, and explains how production flexibility stabilizes non-storable commodity prices similar to how storage ability stabilizes traditional commodity prices.[7]

[7]In storable commodity markets, production can remain constant at the average demand, since excess supply

4 Econometric Specification

To test the implications and conclusion from the theoretical model in Section 3, I take advantage of high-frequency wholesale electricity price data at the hourly level. Hourly data are collapsed into daily observations which include intra-day price volatility, intra-day demand volatility, and daily average demand. The theoretical model from Section 3 implies a reduced form econometric specification where the intra-day price volatility is a function of natural gas capacity, intra-day demand volatility, daily average demand, and unobservable time trends. Thus, the model is:

$$v_t = \beta_0 + \beta_1 NGC_t + \beta_2 S_t + \beta_3 D_t + \beta_4 T_t + \varepsilon_t \quad (5)$$

where v_t is the intra-day price volatility (as measured through intra-day standard deviation) on day t, NGC_t is total natural gas capacity, S_t is intra-day demand volatility, D_t is mean demand, T_t is a vector of unobservable time fixed effects, and ε_t is a serially correlated error term such that $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$ where u_t is random noise. The vector of unobservable time fixed effects T_t includes month fixed effects and day-of-week fixed effects to capture additional unobservable seasonality that is not captured by daily demand. It also includes a linear time trend variable, as well as year fixed effects to capture non-linear time trends. Both mean demand and intra-day demand volatility are assumed to be exogenous to price and intra-day price variance because of the focus on the wholesale market. As discussed in Section 2, retail residential consumers face no price pressures in the short term from the wholesale market because they are billed on a monthly level using a regulated rate instead of the average wholesale market rate. Instead, the primary drivers of daily demand are weather, season, and hour-of-day.

Due to the stepwise increases in capacity from new additions, the preferred specification is a pooled event study using the model above. In this specification, each natural gas capacity change is accompanied by a separate event window fixed effect in an ordinary least squares (OLS) regression. The event window chosen for this analysis includes one month before and after the capacity change, and assumes the exact date of the capacity change is exogenous within this small window. This arguably alleviates endogeneity concerns surrounding natural

can be stored and sold in a later period. This means that ramping costs and demand volatility can be pushed to zero because the residual demand across different periods are pushed to their aggregate mean. Thus, prices are stabilized at their marginal production costs.

gas capacity and price, which arise since natural gas units are usually the marginal generating unit and typically determines the marginal price of electricity in the wholesale market. Thus, it is likely that running a simple OLS regression without the event window fixed effects is inadequate because natural gas capacity is endogenous with electricity price and intra-day price variance.

However, if the assumption that capacity comes online exogenously within the event window is not valid, I also provide an instrumental variables approach using a two-stage least squares (2SLS) regression. In this alternative approach, I instrument for natural gas capacity using a 31-day rolling average of the "spark spread", lagged by 24 months. The spark spread is the gross margin between electricity price and the cost of generation using natural gas. More specifically,

$$SS_t = \sum_{i=0}^{30} \frac{1}{31}(p_{t-i} - NGP_{t-i} * HEAT_{t-i}) \tag{6}$$

where SS_t is the 31-day rolling average spark spread (\$USD/MWh) on day t, p_t is the daily average electricity spot price (\$USD/MWh), NGP_t is the natural gas price (\$USD/MMBtu), and $HEAT_t$ is the heat rate (MMBtu/MWh) which measures how efficiently a natural gas generator can convert gas into electricity. The spark spread gives a measure of the profitability of generating electricity from natural gas and is highly relevant for investment decisions surrounding natural gas capacity. Further, a lagged spark spread is used as an instrument because it is intuitively correlated with future natural gas capacity, but is exogenous with respect to current prices. While some persistence in the spark spread may cause autocorrelation to remain at short intervals, at longer intervals this is shown to not be the case. Thus, a 24-month lag is used in the model. The long lag is due to a natural gas construction time of 18-36 months and should pass the exclusion restriction which requires the instrument to only influence current electricity prices through natural gas capacity.

Finally, a third specification is provided using a generalized autoregressive conditional heteroskedasticity (GARCH) model (Bollerslev, 1987, Engle, 1982), which is sometimes used in the literature on electricity prices and volatilities (Hadsell et al., 2004, Worthington et al., 2005, Hadsell, 2007). In brief, the conditional intra-day volatility estimated by the GARCH model is

$$p_t = \phi + \varepsilon_t \tag{7}$$

$$v_t = \beta_0 + \beta_1 v_{t-1} + \beta_2 \varepsilon_{t-1} + \beta_3 NGC_t + \beta_4 S_t + \beta_5 D_t + \beta_6 T_t \tag{8}$$

where v_t is the intra-day price volatility (as measured through intra-day standard deviation) on day t, such that v_{t-1} represents the previous period's volatility forecast. Meanwhile, ε_{t-1} is a lagged error term representing new information about volatility from the previous period. Similar to prior specification, NGC_t is total natural gas capacity, S_t is intra-day demand volatility, D_t is mean demand, T_t is a vector of unobservable time fixed effects, p_t is electricity price, and ϕ is mean electricity price. The GARCH model also requires the dependent variable to generated by a stationary process, so an augmented Dickey-Fuller test is performed. I reject the null hypothesis that intra-day price volatility contains a unit root with a z-statistic of -29.00 and I reject that mean price contains a unit root with a z-statistic of -14.48. Thus, the additional requirements to use the GARCH model are satisfied by my price data during my study period.

5 Data

To test the role of natural gas capacity in the price stability of the wholesale electricity market, I use data from the Independent Systems Operator of New England (ISO-NE). Hourly electricity prices from the real-time ISO-NE market are obtained from March 2005 through June 2011. Throughout the analysis, prices and electricity demand loads are taken from the Southeast Massachusetts (SEMASS) zone, as it is geographically central to the ISO-NE. The data for both price and demand load are collapsed at the daily level to provide intra-day volatility for the 24-hour period.

Although "volatility" is colloquially used to imply "variability," for clarity I define volatility as the standard deviation of the data.[8] More formally:

$$\sigma_t^x = \sqrt{\frac{1}{24}\sum_{h=1}^{24}(x_{t,h} - \mu_t)^2} \tag{9}$$

where σ_t^x is intra-day volatility for the variable x on day t, h is the hour of day, and μ is the daily average of x. Thus, throughout the remainder of the analysis I use the terms "volatility" and standard deviation interchangeably.

[8]This is also sometimes referred to as "historical volatility" in the finance literature, which is distinct from annualized volatility, implied volatility, variance, and the probability of extreme events.

Monthly summary statistics are shown in Table 3 for daily mean price, intra-day price volatility, daily mean demand, and intra-day demand volatility. The summary statistics are consistent with previous expectations about the New England electricity market, with the summer and winter months showing higher intra-day volatilities in addition to higher mean prices, mean-demands, and intra-day demand volatilities. The summary statistics suggest a strong seasonality to all variables of interest, which will be important to capture through month fixed effects.

Table 3: Summary Statistics for ISO-NE (March 2005 through June 2011)

		Mean and Std. Dev. (in parentheses)			
Month	Obs (n)	Daily Mean Price ($USD/MWh)	Intra-Day Price Volatility ($USD/MWh)	Daily Mean Demand (MWh)	Intra-Day Demand Volatility (MWh)
January	186	69.07	18.92	1,791.5	278.4
		(21.42)	(10.35)	(107.0)	(33.6)
February	169	62.99	16.02	1,764.2	254.7
		(16.81)	(8.13)	(108.1)	(33.5)
March	217	55.76	13.30	1,667.7	246.6
		(16.74)	(7.58)	(118.4)	(43.0)
April	210	56.43	12.75	1,532.0	239.7
		(20.71)	(8.25)	(91.3)	(37.3)
May	217	58.83	15.71	1,552.9	267.9
		(23.99)	(11.42)	(113.7)	(47.4)
June	210	58.66	16.65	1,813.6	354.0
		(25.37)	(12.58)	(246.3)	(91.1)
July	186	64.70	18.39	2,100.6	425.8
		(26.90)	(11.84)	(284.2)	(99.7)
August	186	63.83	19.81	2,048.3	409.8
		(27.30)	(30.82)	(284.4)	(100.6)
September	180	58.63	16.11	1,722.6	319.6
		(24.94)	(11.69)	(197.3)	(67.6)
October	186	59.51	15.38	1,586.6	278.8
		(26.68)	(13.38)	(100.3)	(36.6)
November	180	55.85	14.80	1,623.5	284.0
		(15.02)	(8.23)	(86.6)	(32.2)
December	186	71.17	18.49	1,794.0	303.3
		(24.15)	(9.11)	(116.4)	(38.2)
Total Sample	2313	61.11	16.28	1744.7	304.1
		(23.34)	(13.42)	(242.2)	(84.5)

Figure 3 shows a clear relationship between intra-day price volatility and intra-day demand volatility. The graph uses a 60-day smoothing average to show general time trends without the daily statistical noise. The seasonality of intra-day demand volatility comes through very clearly, with a strong peak during the summer months and a second, smaller peak during early

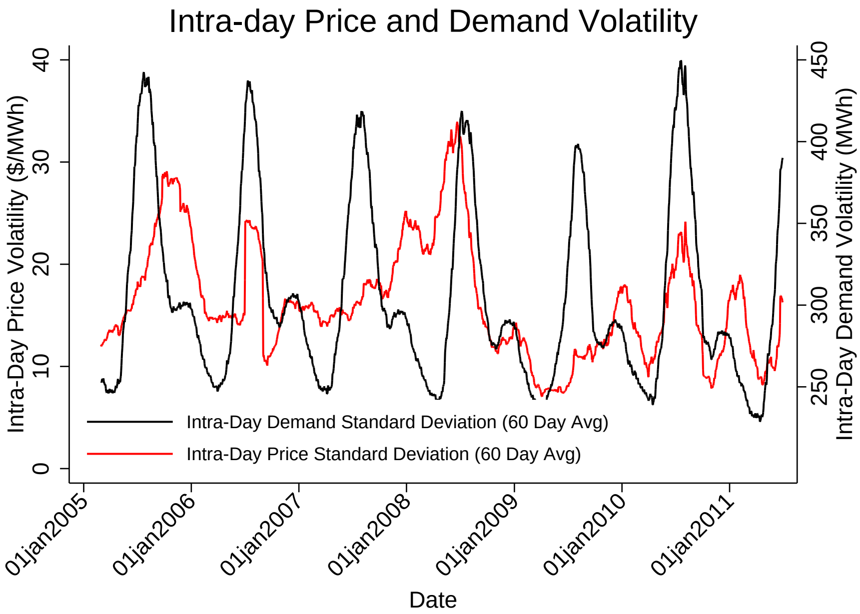

Figure 3: Intra-day Price and Demand Volatility

winter. An overall linear time trend is less obvious for either price or demand volatility, but there may be a slight decrease in both intra-day volatilities over time. Generally, periods of high demand volatility appear to coincide with high price volatility, a finding consistent with the intuition of the theoretical model in Section 3.

Figure 4 shows a similar trend, again with a clear seasonality for both daily mean demand and intra-day price volatility. The second peak during early winter is more pronounced in the mean demand graph than in the intra-day demand graph, but the two graphs are generally consistent with each other. As implied by the basic and intuitive theoretical model, the temporal patterns of volatility and mean demand are highly correlated.

Data on natural gas generator heat rates and Massachusetts gas price are taken directly from the United States Energy Information Agency (EIA). Since heat rate data is provided by the EIA only at annual averages through their "Electric Power Annual Report" (EIA, 2013*b*), a monthly rolling average is constructed which assumes linear technological improvements within the year. The EIA also provides monthly average natural gas prices paid by Massachusetts power plants using data from their "Monthly Cost and Quality of Fuels for Electric Plants Report" (form EIA-423) and "Power Plant Operations Report" (form EIA-923). The monthly data is then used to construct the marginal cost of electricity from natural gas, without considering

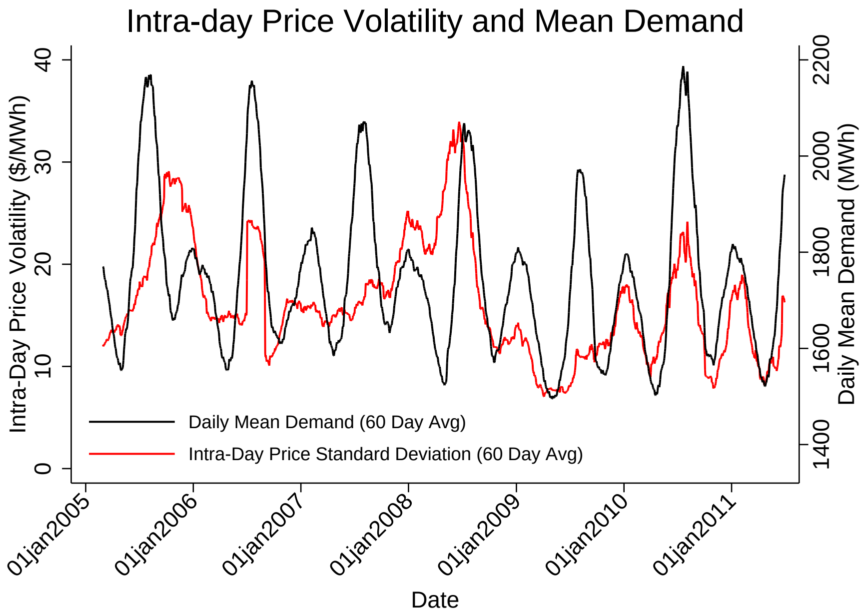

Figure 4: Intra-day Price Volatility and Mean Demand

operational expenses. Finally, a daily spark spread is constructed as the difference between the daily average electricity spot prices within the SEMASS zone and the marginal cost of electricity from natural gas, as described in Section 4.

Summary statistics for all variables used to construct the spark spread are shown in Table 4. As expected, the average heat rate improves over time from 9,207 Btu/kWh in 2003 to 8,159 Btu/kWh in 2009. Note that the heat rate data covers from March 2003 through June 2009, although the primary period of this analysis is from March 2005 through June 2011. This is because of the 24-month lagged spark spread used as the instrumental variable for natural gas capacity. Thus, the data from March 2003 through February 2005 is only used to calculate the instrumental variable and is not used as the dependent variable in the primary regression results of Section 6.

Table 4: Instrumental Variable Construction (March 2003 through June 2009)

Variable	Mean	Std. Dev.	Min	Max
Heat Rate (Btu/kWh)	8548	290.5	8159	9207
MA Gas Price ($USD/1000 ft^3)	7.924	2.378	4.30	14.76
Electricity Cost from Gas ($USD/MWh)	65.62	19.01	34.23	122.39
Daily Average Price ($USD/MWh)	62.00	22.24	22.48	277.80
Spark Spread ($USD/MWh)	-3.62	14.70	-62.07	210.73

The natural gas price paid by Massachusetts power plants during this period is \$7.9 per thousand cubic feet. This is expected, although it is slightly above the United States average of \$7.19 paid by power plants from March 2003 through June 2009. After calculating the marginal cost of electricity from the natural gas prices and the EIA average heat rates, the daily average is \$65.62 per megawatt-hour. As expected, this is very close to the mean spot price during this period (\$62/MWh) because natural gas generators are typically the marginal generator and thus set the electricity price. The difference between these leads to a small average spark spread of -\$3.62/MWh.

While a trivial average spark spread is expected it is also important to note the large variation. During the sample period, the daily average spark spread runs from -\$62/MWh to \$211/MWh. Further, many natural gas generators are "load following units" meaning that they ramp up generation to follow the increased demand during peak hours of the day when prices and demand are highest. The relatively low ramping costs of natural gas units means they can selectively operate during profitable hours. Thus, it is certainly possible to make a profit using natural gas generators even though the small negative daily average spark spread initially suggests otherwise. Further, the 31-day rolling average spark spread that is used as an instrument smooths away from daily noise and remains a good measure of overall profitability for natural gas units. If the spark spread average remains high for some time, the increased profitability will induce additional entrants to build capacity. Thus, a positive spread should encourage new investment in natural gas capacity.

Data on natural gas capacity is gathered from the EIA's "Annual Electric Generator Report" (form EIA-860). The dataset includes generator level data for power plants in the United States and includes the state of operation, nameplate capacity, date placed in service, and date retired when it applies. Generator level data is collected for all six states within the ISO-NE and changes in natural gas capacity are constructed for 2005-2011 using installation and retirement dates. During this period total natural gas capacity in the EIA database increased by 730.1 MW, which amounts to just over 6% of installed natural gas capacity in 2010 (FERC, 2010). The additions came through nineteen new generators, with an average capacity of 60 MW each. These additions happened through thirteen new power plants, with an average capacity of 87 MW each. Further variations in total capacity come from the nine natural gas generator

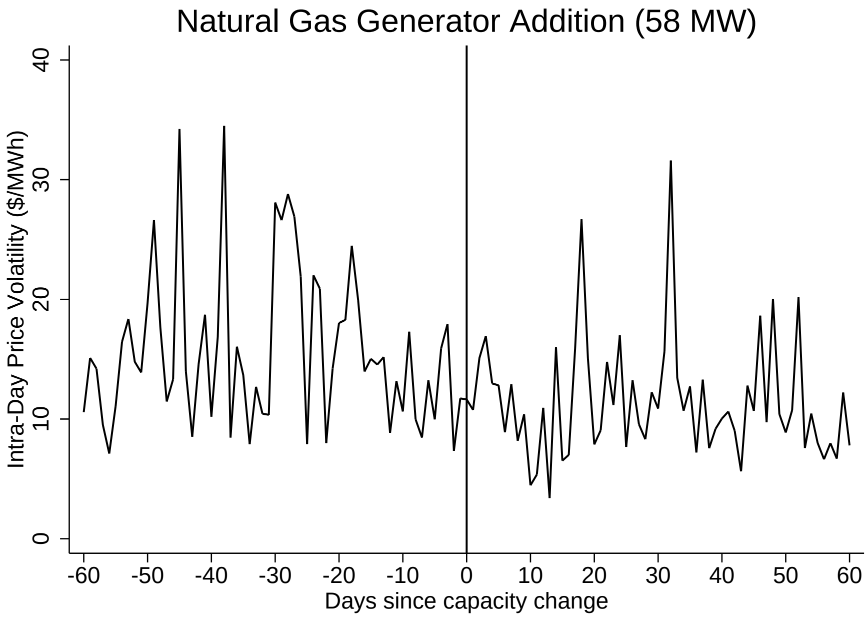

Figure 5: Example of natural gas generator addition

retirements, with an average capacity of 45 MW each. These capacity reductions happened through the closure of seven power plants, with an average capacity of 58 MW each.

As a visual example of a capacity event, Figure 5 graphs intra-day volatility over time, where the x-axis shows the number of days from the day of the capacity addition. The event shown is a 58 MW natural gas generator addition, which was chosen because it represents the average size of a capacity change from 2005-2011. As the graph demonstrates, intra-day volatility is generally noisy, although volatility does appear to decrease in the period following the capacity change.

While no new nuclear capacity has been installed or retired during the period studied, nuclear capacity occasionally goes offline for both planned and unplanned outages related to refueling, maintenance, and safety. Planned outages are typically scheduled months in advance and occur during regular refueling times. As such, the exact outage date is arguably exogenous with respect to the current intra-day price volatility, but the data is also analyzed using unplanned "forced outages" with no change to the results discussed in Section 6. Data on nuclear capacity outages within the ISO-NE comes directly from the US Nuclear Regulatory Commission's "Power Reactor Status Report." There are five active nuclear generators within the four nuclear power plants located inside the ISO-NE load area.[9] The generators have an average capacity of 917 MW per generator, for a total installed nuclear capacity of 4,586 MW. During the sample period, the average active installed capacity is 4,217 MW, such that active capacity was below installed capacity for 391 total days, or 17% of the sample. Included among these are 185 days from forced outages, or 8% of the total sample days. Since there are overlapping outages, perhaps a more insightful statistic during the sample period is an average outage time of 21.9 days per nuclear generator per year.

6 Results

The regression results show that natural gas capacity significantly decreases intra-day price volatility in the wholesale electricity market, supporting the theoretical model in Section 3. Table 5 provides the coefficients of interest for each of the three primary specifications, with Newey-West standard errors reported when applicable to correct for serial correlation. Column (A) is the preferred specification, using the pooled event study approach. Column (B) gives the second stage results for the two-stage least squares (2SLS) specification. Finally, Column (C) provides the regression results for the generalized autoregressive conditional heteroskedasticity (GARCH) model. As discussed in Section 4, each specification controls for intra-day demand volatility, daily demand means, month fixed effects, year fixed effects, day-of-week fixed effects, and linear time trends.

The results across all three specifications continually show natural gas capacity leading to a significant decrease in price volatility. The coefficient in Column (A) suggests that each additional MW of natural gas capacity decreases price volatility by \$0.010/MWh. The average generator addition during my sample period is 60 MW, so the results suggest that a typical generator addition decreases intra-day price volatility by about 4%, or \$0.62/MWh. This volatility decrease is approximately 1% of the mean electricity price during the sample period. The 2SLS results in Column (B) show an increase in the magnitude of natural gas coefficient to -0.028, thought this is not statistically different from the pooled event study regression in Column (A). Using the 2SLS coefficient instead suggests that adding an additional natural gas gener-

[9] The four power plants are Millstone Nuclear Power Station in Connecticut, Pilgrim Nuclear Generating Station in Massachusetts, Seabrook Nuclear Power Plant in New Hampshire, and Vermont Yankee Nuclear Power Plant in Vermont.

Table 5: Regression Results: Natural Gas Capacity
Dependent Variable: Intra-day Price Volatility ($/MWh)

	(A) OLS	(B) 2SLS	(C) GARCH
Natural Gas Capacity (MW)	-0.0103**	-0.0278**	-0.0099***
	(0.0051)	(0.0109)	(0.0025)
Demand Volatility (MWh)	0.0622***	0.0629***	0.0552***
	(0.0071)	(0.0068)	(0.0037)
Demand Mean (MWh)	0.0159**	0.0161***	0.0149***
	(0.0067)	(0.0026)	(0.0015)
Time Fixed Effects	Yes	Yes	Yes
Observations	2313	2313	2313

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis for Columns (A) and (B) to correct for serial correlation.

ator decreases intra-day price volatility by about 10%, or $1.66/MWh. Finally, the GARCH model gives a coefficient of -0.011 in Column (C), insignificantly different from either of the two previous specifications.

All three specifications continually show that intra-day price volatility significantly increases with both intra-demand volatility and mean demand, after considering seasonality and time trends. This is again consistent with the expectations of the theoretical model. Further, the marginal effect of an increase in demand volatility has a much larger effect than an increase in daily mean, as is intuitively expected since intra-day demand volatility is a main driver of the intra-day price volatility. While there are small changes in the coefficients across models, these differences are not statistically different.

To assess the robustness of the 2SLS results in Column (B) of Table 5, variations on the spark spread are used and the first stage results are reported in Table 6. Columns (A), (B), and (C) coincide with the same columns of the second stage in Table 7. As expected, the lagged spark spread is strongly correlated with increases in natural gas capacity. In Column (A), the spark spread used is lagged two years and is a 31-day rolling average as in Column (B) of Table 5. I also perform a weak instrument test using the rk-statistic of Kleibergen and Paap (2006) because the F-statistic of Cragg and Donald (1993) is not valid when the standard errors are not *i.i.d.* normal. Previous literature suggests a rule of thumb where there is little concern of a weak instrument with an F-statistic above 8.96 (Stock and Yogo, 2001, Stock et al., 2002). The preferred specification in Column (A) of Table 6 shows that the lagged spark spread is

Table 6: First Stage 2SLS Results
Dependent Variable: Natural Gas Capacity (MW)

	(A)	(B)	(C)
Lagged Spark Spread ($/MWh)	4.526***	4.624***	4.219***
	(0.349)	(0.403)	(0.432)
Time Fixed Effects	Yes	Yes	Yes
Kleibergen-Paap rk-statistic	167.87	131.21	95.14
Observations	2313	2313	2313

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

Table 7: Second Stage 2SLS Results
Dependent Variable: Intra-day Price Volatility ($/MWh)

	(A)	(B)	(C)
Natural Gas Capacity (MW)	-0.0278**	-0.0380***	-0.0496***
	(0.0109)	(0.0123)	(0.0146)
Demand Volatility (MWh)	0.0629***	0.0630***	0.0632***
	(0.0068)	(0.0069)	(0.0070)
Demand Mean (MWh)	0.0161***	0.0159***	0.0157***
	(0.0026)	(0.0026)	(0.0027)
Time Fixed Effects	Yes	Yes	Yes
Observations	2313	2313	2313

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

arguably a very strong instrument, with a Kleibergen-Paap rk-statistic of 167.87.

The regression results shown in Columns (B) and (C) use a 60-day and 90-day rolling average for the lagged spark spread instead of a 31-day average. The results are not particularly sensitive to the number of days included in the rolling average of the spark spread. The marginal effects are not statistically different from Column (A), although they do increase. The first stage results in Table 6 show that the instrument remains strong and yields no significant change in magnitude.

As discussed in Section 3, there are two effects of adding natural gas capacity. First, is the outward shift in the supply curve which should yield a decrease in intra-day price variance because demand intersects on a flatter convexity. The second effect is the decrease in ramping costs which squeezes together the dynamic supply curve shifts, which also yields a decrease in intra-day price variance. The regression above captures both of these effects, but the ramping costs effect is of particular interest to this paper. It is arguably possible to separate out these

Table 8: Regression Results: Natural Gas and Nuclear Capacity
Dependent Variable: Intra-day Price Volatility ($/MWh)

	OLS (A)	OLS (B)	OLS (C)	2SLS (D)	GARCH (E)
Natural Gas Capacity (MW)			-0.0152**	-0.0347***	-0.0166***
			(0.0059)	(0.0120)	(0.0025)
Nuclear Capacity (MW)	-0.0013***	-0.0014***	-0.0019***	-0.0026***	-0.0019***
	(0.0004)	(0.0005)	(0.0006)	(0.0007)	(0.0002)
Nuclear Capacity X Forced Outage (MW)		0.0001			
		(0.0004)			
Demand Volatility (MWh)	0.0626***	0.0626***	0.0628***	0.0632***	0.0554***
	(0.0072)	(0.0072)	(0.0071)	(0.0068)	(0.0036)
Demand Mean (MWh)	0.0167**	0.0167**	0.0160**	0.0164***	0.0144***
	(0.0071)	(0.0071)	(0.0067)	(0.0026)	(0.0015)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	2313	2313	2313	2313	2313

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

two effects using capacity changes that only affect volatility through outward supply curve shifts, for example using nuclear outages. Since nuclear power is a low marginal cost provider of baseload power and does not typically ramp production during the day, it seems reasonable to assume that nuclear power outages will only shift the supply curve inward, without changing the intra-day dynamics involved from ramping costs. Thus, running the same specification on nuclear power should show changes in volatility due only to the supply curve shift. As previously noted, no new nuclear capacity has been built during the time period studied but outages do occur for refueling, planned maintenance, and occasional emergency shutdowns. The specifications shown in Table 8 use these temporary outages in nuclear capacity to understand the volatility changes from the supply shift. The OLS results in Column (A) show a small but statistically significant decrease to price volatility from nuclear capacity. The marginal effect of an additional MW of nuclear capacity leads to a $0.0013/MWh decrease in intra-day price volatility. Although nuclear outages are generally assumed to be exogenous, Column (B) uses an interaction effect between nuclear capacity and forced outages to ensure that forced outages behave similarly to planned outages. The results show that forced outages have a very small, insignificantly different effect on intra-day price volatility when compared to regular outages.

Columns (C), (D), and (E) of Table 8 include natural gas capacity outages in the same regression and can be compared with Columns (A), (B), and (C) of Table 5. The pooled event study approach is shown in Column (C) of Table 8 while the 2SLS and GARCH models are shown in Columns (D) and (E), respectively. When including the capacities of both nuclear and natural gas power plants, the marginal effect of natural gas and nuclear capacity on price volatility changes insignificantly across specifications.

As discussed above, the discrepancies in the marginal effect between nuclear capacity and natural gas capacity are attributed to ramping costs. The preferred results in Column (C) suggest that adding 60 MW of nuclear capacity decreases intra-day price volatility by 0.7%, or \$0.114/MWh, while adding 60 MW of natural gas capacity decreases intra-day price volatility by 5.6%, or \$0.912/MWh. Thus, empirically it appears that the reduction of volatility from the supply shift effect is actually quite small, although still statistically significant. The bulk of the volatility reduction from adding natural gas generators comes through supply flexibility via decreased ramping costs. The results imply that adding 60 MW of natural gas capacity will decrease intra-day price volatility by 4.9 percentage points, or \$0.798/MWh, more than adding a lower marginal cost inflexible generator. This volatility reduction amounts to approximately 1.3% of the mean electricity price.

The theoretical model also implies the ramping cost effect to be greater during the summer months for two reasons. First, the ramping cost effect is more pronounced because demand intersects a steeper section of the convex supply curve. Second, demand volatility is greater during the summer months which also induces larger dynamic shifting of the supply curves. This notion is tested empirically in Table 9 using the pooled event study, 2SLS, and GARCH models in Columns (A), (B), and (C), respectively.

Each column of Table 9 uses an interaction effect with a dummy variable equal to one during the summer months of June through August, when demand and intra-day demand volatility are highest. Consistent with our expectations, each regression shows that natural gas capacity provides a significantly larger stabilizing effect during the summer. Meanwhile, the supply shift effect shown by the coefficient on nuclear capacity is also larger during the summer months but it is again an order of magnitude below that of natural gas. This effect is only significant in the first two columns. While the size of the coefficients for natural gas and nuclear does change across specification, they all are consistent with the intuition of the theoretical model which implies larger volatility reductions in the summer months due the the ramping cost effect.

Table 9: Regression Results: Natural Gas and Nuclear Capacity
Dependent Variable: Intra-day Price Volatility ($/MWh)

	(A) OLS	(B) 2SLS	(C) GARCH
Natural Gas Capacity (MW)	-0.0105*	-0.0391***	-0.0123***
	(0.0060)	(0.0144)	(0.0025)
Natural Gas Capacity X Summer (MW)	-0.0351***	-0.0225***	-0.0171***
	(0.0050)	(0.0053)	(0.0027)
Nuclear Capacity Capacity (MW)	-0.0019***	-0.0027***	-0.0018***
	(0.0005)	(0.0007)	(0.0002)
Nuclear Capacity Capacity X Summer (MW)	-0.0047*	-0.0049*	0.0009
	(0.0024)	(0.0026)	(0.0012)
Time Fixed Effects	Yes	Yes	Yes
Observations	2313	2313	2313

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

Figure 6 shows the monthly marginal effect of additional natural gas capacity on intra-day price volatility. Although segmenting the sample by months limits statistical significance because of a smaller sample size, the relative coefficient magnitudes are revealing. There is a clear intra-year trend, with natural gas providing larger reductions to price volatility during months with larger demand volatility. Consistent with the regression in Table 9, the decrease in volatility from natural gas capacity in the summer months is several times greater than the rest of the year.

This has important implications for future price behavior in the presence of non-dispatchable wind or solar generation. While wind generation will reduce the residual demand that is supplied by conventional generators, it also has intermittency concerns that may increase the demand volatility served by conventional generators. Solar has similar concerns but the effect is more ambiguous since production follows demand, with larger output during the summer and daylight hours. Thus, the results in Table 9 and Figure 6 underscore the importance of pairing increases in intermittent renewable generators with conventional generators that have low ramping costs. The results suggest that the value of price stability from natural gas is increasing with the share of non-dispatchable generators such as wind, an idea explored further in Section 7.

While this analysis yields strong evidence that the low ramping costs of natural gas generators provide ancillary benefits to intra-day price stability, this may not be the case at longer time intervals. At the intra-day level, natural gas generators arguably are not subject to fossil

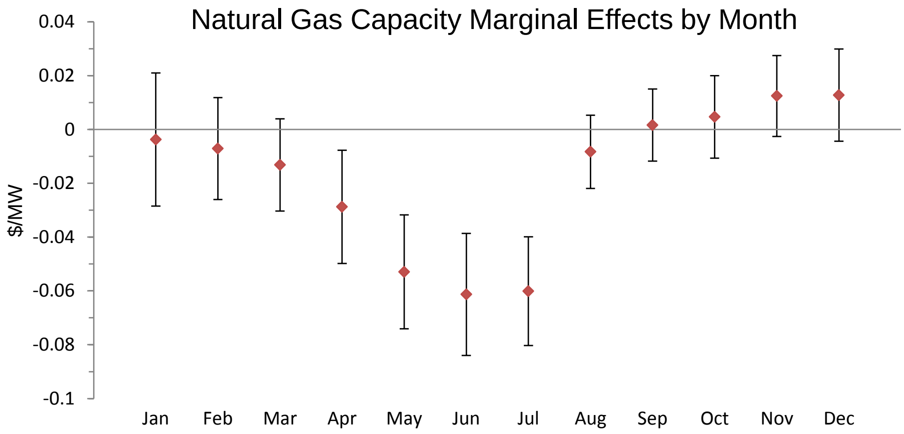

Figure 6: Natural Gas Capacity Marginal Effects by Month

fuel price volatility since gas prices paid by generators are often negotiated through bilateral contracts and forward financial markets. However, at longer time horizons natural gas generation is subject to fossil fuel price volatility which means the price stability benefits shown here at the daily level may not translate to volatility reductions at the monthly level.

To investigate this notion, an analysis identical to the baseline specification is performed using the same data at the monthly aggregation. The results of natural gas capacity on intra-month spot price volatility are shown in Table 10. The results show that increases in natural gas capacity lead to reductions in intra-month price volatility similar in magnitude to the daily reductions. However, the results are no longer statistically significant. This is arguably the result of both a smaller sample size and larger variations in fossil fuel prices which suppress the price stability benefits shown at the daily level. The results suggest that the ancillary pecuniary benefits from natural gas at the intra-day level do not necessarily generate benefits at longer time horizons. Finally, they emphasize the importance of disaggregated data analysis when investigating electricity markets and related price behavior.

As an additional robustness check to the intra-day price volatility analysis, I perform the same regression using an alternative measure of volatility that is also used in finance literature focused on electricity prices (Simonsen, 2005, Hadsell and Shawky, 2006, Zareipour et al., 2007, Ullrich, 2012, Haugom and Ullrich, 2012*a*). Here, the historical volatility is defined as the standard deviation of the logarithmic returns:

$$\sigma_t^r = \sqrt{\frac{1}{24}\sum_{h=1}^{24}(r_{t,h} - \overline{r_t})^2} \tag{10}$$

Table 10: Regression Results: Intra-month Volatility
Dependent Variable: Intra-month Price Volatility ($/MWh)

	(A) OLS	(B) 2SLS	(C) GARCH
Natural Gas Capacity (MW)	-0.0327	-0.0338	-0.0102
	(0.0213)	(0.0229)	0.0206
Demand Volatility (MWh)	0.1203	0.1517***	0.1048*
	(0.0939)	(0.0563)	(0.0630)
Demand Mean (MWh)	-0.0179	-0.0118	0.0115
	(0.0551)	(0.0256)	(0.0279)
Time Fixed Effects	Yes	Yes	Yes
Observations	76	76	76
Kleibergen-Paap rk-statistic		28.53	

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

Table 11: Regression Results: Alternative Volatility Measure
Dependent Variable: Standard deviation of logarithmic returns

	(A) OLS	(B) OLS	(C) 2SLS	(D) 2SLS
Natural Gas Capacity (100 MW)	-0.0129***	-0.0126***	-0.0226**	-0.0212**
	(0.0047)	(0.0047)	(0.0094)	(0.0097)
Nuclear Capacity (100 MW)		0.0005		0.0007
		(0.0007)		(0.0008)
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,313	2,313	2,313	2,313
Kleibergen-Paap rk-statistic			150.52	140.52

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

where σ_t^r is the intra-day volatility of logarithmic returns on day t and h is the hour of day. Logarithmic returns are defined as

$$r_{t,h} = ln\left(\frac{p_h}{p_{h-1}}\right) \tag{11}$$

where p_h is electricity price for hour h on day t.

Over the entire sample period, intra-day standard deviation of logarithmic returns is 0.2047 and the daily mean returns are close to zero, as expected, at -0.0040. While the intra-day volatility of returns is quite high, it is consistent with the range found in the previous literature which use this measure (Zareipour et al., 2007).

The regression results for both the pooled event study and the 2SLS specification are shown in Table 11 all models include mean daily demand, intra-day demand volatility, month fixed effects, day of the week effects, and a linear time trend. The results are similar to the primary results, with natural gas capacity significantly reducing price volatility. Again, the coefficient on natural gas is an order of magnitude above the coefficient for nuclear capacity for the specifications in Columns (B) and (D). Across all specifications the coefficient for natural gas capacity are not significantly different from each other, while the coefficient on nuclear capacity is insignificantly different from zero. A 60 MW natural gas generator addition will decrease volatility by 0.008, or approximately 3.9%. This is only slightly below the results of previous tables when using the traditional definition of volatility which estimates the typical natural gas generator will reduce intra-day volatility by 5.6%.

7 Consequences for Option Pricing

The reduction in daily volatility is especially important for risk averse power purchasers. Since electricity retailers face a fixed sale price to end users, they may hedge away from spot price risk through purchasing delivery contracts in the day-ahead market. The value of volatility reductions due to natural gas capacity can be captured through an option to buy electricity in a forward market. Since the volatility reductions from natural gas capacity are due to their ancillary services as indirect electricity storage, the option value provides an estimation of the storage value of electricity from natural gas generators. To quantify the value of such an option, I use the seminal model developed by Black and Scholes (1973).

The Black-Scholes model provides a simple and common valuation of options, given a current asset price, exercise price, time to maturity, risk-free interest rate, and annualized volatility. I assume that the 0.14% return on one-year US Treasury bills is an appropriate proxy for the risk-free interest rate, as is common in asset valuation. Other assumptions include a one-day maturity time with no trading opportunities between days. It is reasonable to assume no trading opportunities between days because the electricity scheduled for delivery in hour h is a separate asset than electricity delivered in hour j, for all $h \neq j$. Thus, the annualized volatility input into the model is equivalent to the intra-day standard deviation of logarithmic returns in Section 6. Lastly, it is assumed that the option in question is equivalent to a fixed price contract, hedging away from all price risk such that the daily mean electricity price is used for both the current asset price and the exercise price.

I calculate the described option to be valued at \$0.237/MWh, which amounts to approximately 0.4% of the average daily price. Using the most conservative marginal effect from Section 6, adding a 60 MW natural gas generator will decrease volatility by 3.9%, from 0.2047 to 0.1970. Thus, the price of the new option drops approximately 3.8% to \$0.228/MWh. The difference of \$0.009/MWh is interpreted as the market value of a volatility reduction from a 60 MW natural gas generator. Although this difference appears to be a small portion of the electricity price per MWh, the ISO-NE transmitted 129,158 GWh in 2011 (ISO-NE, 2011). Thus, assuming power purchasers fully hedge away from spot price risk in the day-ahead market, the value of reduced volatility from a single 60 MW natural gas generator amounts to approximately \$1.13 million annually. This can also be interpreted as the indirect storage benefit provided annually by the marginal natural gas generator in the New England market.

While \$1.13 million annual benefits appears small relative to the \$6.17 billion in 2011 electricity expenditures within the ISO-NE, a 60 MW generator represents only a small fraction of the 30 GW installed capacity within the ISO-NE region. In fact, the volatility reduction is quite large from a single generator, representing approximately 1.6% of its construction costs when using a \$1.2 million per MW basis seen in recent natural gas power plant construction costs (CPV, 2013).

The benefits described here accrue to power purchasers, but may not represent a dead weight loss because there is presumably a risk-neutral party profiting on the other side of the option. Instead, with the assumption that costs of electricity are fully passed from utilities to consumers, the annual benefits accrue to consumer surplus. Thus, a marginal increase of the average sized natural gas generator leads to a \$1.13 million annual increase in consumer surplus from the volatility reduction alone. This back of the envelope calculation does not consider additional externalities such as the macroeconomic value from greater grid stability, the ability to operate reliably on a lower reserve margin due to more flexible production, or the environmental costs of pollution.

7.1 Option Value Simulation

To explore how the option value of additional natural gas capacity explores over time within the ISO-NE, I provide a simple simulation which is calibrated using the coefficients from the econometric model results. Internal reports by the ISO-NE note that over two-dozen oil and coal fired generators may be retired within the next decade. If these aging generators do retire, ISO-NE notes that over 6,000 MW of new capacity will need to be produced. A significant percentage of the replacement capacity will come from natural gas generators, and up to 40% of proposed projects are from wind generation (ISO-NE, 2013). Using these retirements to motivate the context, the simulation shows how the option value of additional natural gas capacity changes over time.

First, the impact on price volatility from wind generation is recovered from the marginal effects in Section 6. Wind generation is a non-dispatchable resource, so additional wind capacity can be modeled as a decrease in the residual electricity demand that is supplied by dispatchable generators. Further, the intermittency issues over wind can be thought of as increases the intra-day volatility in this residual demand. As noted from the model and regression results, the theoretical effect of wind on price volatility is ambiguous because of these two competing effects. Since the coefficients for demand and intra-day demand volatility are recovered from exogenous changes in demand, they can be interpreted as the true coefficients from a supply increase of wind without traditional endogeneity concerns between supply and price. A similar method can be used to recover the price volatility impact from solar or other non-dispatchable renewable generators, but it is not done here due to New England's limited solar potential and lack of a comparable region to calibrate the model.

To calibrate the simulation to incorporate the effects of wind generation on price volatility, actual hourly wind generation data is taken from the California Independent Systems Operator (CAISO), within the NP15 zone. This zone covers northern California, which the National Renewable Energy Laboratory estimates to have similar wind potential as the ISO-NE region (NREL, 2014) and the simulation assumes to have the same ratio of wind generation to volatility. Actual hourly wind generation data from ISO-NE is not available for use, but CAISO's NP15 zone data is preferred regardless because the market wind penetration is one percentage point larger than that of ISO-NE and will more accurately reflect the wind volatility under the growth described in the ISO-NE simulation.

The CAISO hourly 2012 wind production data show that an average 0.47 MWh intra-day volatility increase accompanies every MWh decrease in the daily mean residual demand due to wind. This ratio is used in combination with the demand and demand volatility marginal effects to calculate a net increase in price volatility of approximately 3% from 60 MWh of wind energy production. This more accurately reflects the impact of wind generation on price because it is calibrated using wind production, instead of wind capacity, so it already incorporates non-dispatchability concerns such as intermittency and curtailment.

The 3% marginal increase in price volatility due to wind production can be directly compared to the 3.9% decrease in price volatility estimated from the equivalent natural gas production capacity. Their similar magnitudes emphasize their complimentary nature, as the flexible natural gas generation offsets the entire volatility increase from wind power. The ISO-NE envisions a long term future electricity mix of 42% wind and 52% natural gas (ISO-NE, 2013), which is relatively close to the volatility neutral growth of 54.4% wind and 45.6% natural gas calculated by the simulation.

The simulation results are given in Figure 7, which shows how the option value of a typical natural gas generator changes over the next ten years under different generator replacement scenarios that cover the 6,000 MW expected need. The model assumes the aging facilities are phased out linearly and thus replaced at a rate of 600 MW per year. Mean daily demand and intra-day demand volatility are assumed to be constant over time, except as altered through additions of wind capacity.

The four scenarios shown graphically in Figure 7 include assumptions for low natural gas replacement, high natural gas replacement, volatility neutral replacement, and the ISO-NE envisioned scenario. The low natural gas replacement scenario assumes the replacement generators come from 20% wind, 0% natural gas, and 80% other, where "other" is assumed to be a volatility neutral generating source. The high natural gas replacement scenario assumes the replacement generators are 20% wind and 80% natural gas. As described above, the volatility neutral scenario is calculated as replacement generators coming from 54.4% wind and 45.6% natural gas. The fourth scenario uses a replacement rate of 42% wind and 52% natural gas, since this is the ISO-NE envisioned future generation mix.

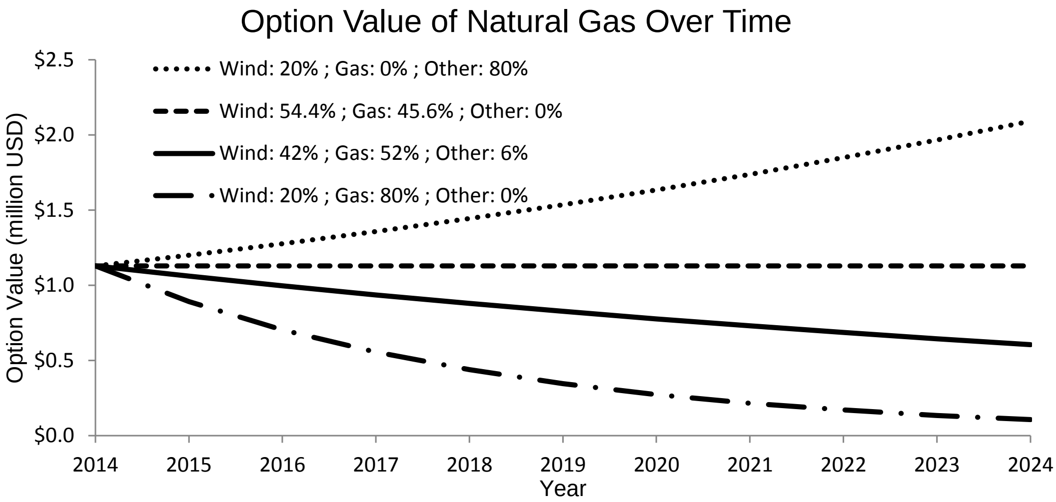

Figure 7: Intra-day Price Volatility and Mean Demand

The simulated option value from the marginal natural gas generator is plotted over time in Figure 7. The low natural gas scenario shows that the marginal option value from a natural gas generator increases over time, approximately doubling to \$2.09 million in the ten year period simulated. This is because the growth of wind increases price volatility in the future, giving a larger value to volatility reductions from natural gas. This is the opposite of the high natural gas scenario, which shows the annual value of natural gas decay over time as the growing share of natural gas decreases the additional need for price stability.

The ISO-NE envisioned future shows a gradual decline in the value of volatility reductions from natural gas generators to \$0.61 million annually. This is due to the growth of natural gas outpacing the growth of wind, which nets to a slow dampening of price volatility. With the decreasing price volatility comes a decrease in the marginal value of volatility reductions from natural gas, as natural gas generators already represent a large share of the market.

To calculate the value of total volatility reductions from a marginal natural gas addition, the model simply integrates under the curves in Figure 7 and discounts the value using standard present value techniques. Thus, the cumulative value from the four scenarios is shown in Figure 8, along with variations in the rate of return used in the option valuation and discount rate. The primary specification uses the one-year Treasury rate of 0.14% for both the risk-free rate of return in the option valuation and also the discount rate in the present-value calculation. The results are also presented using five-year and ten-year Treasury rates of 1.76% and 2.74%, respectively.

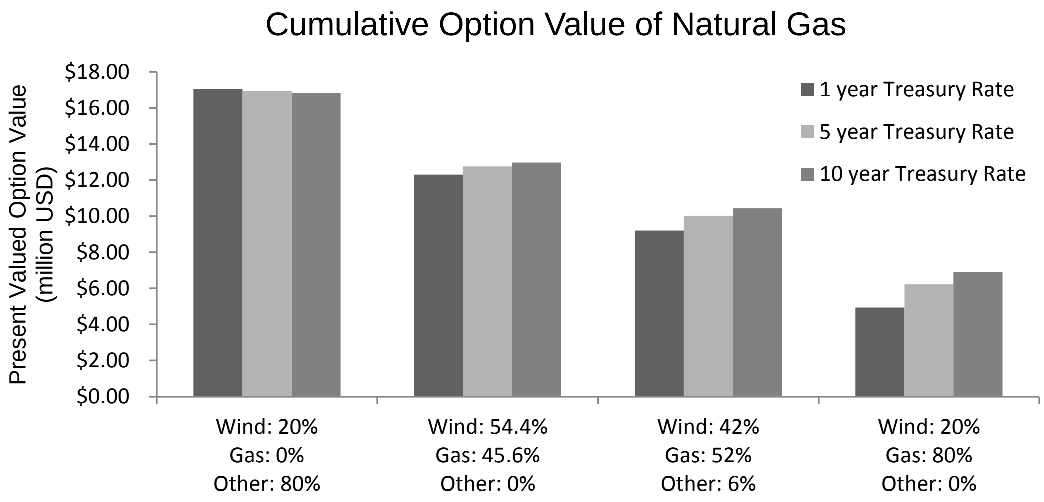

Figure 8: Intra-day Price Volatility and Mean Demand

The cumulative option value of a marginal natural gas generator is shown to vary significantly across the four different scenarios. As expected, the value of natural gas is highest when a large growth in wind generation is unaccompanied by corresponding growth in natural gas capacity. The cumulative value can be over three times as high in this scenario, when compared to a high natural gas growth scenario where growth is four times that of wind. Overall, the simulation results are much more sensitive to the assumed generator growth than to the discount rates used. The cumulative option value varies from $4.9 million to $17 million, but in the ISO-NE envisioned scenario is valued at $9.2 million, or 12% of its construction cost.

8 Natural Gas Capacity and the Forward Premium

Since adding flexible production capacity affects volatility in a similar fashion to electricity storage, there could be implications for the forward premium as well. Douglas and Popova (2008) argue that larger natural gas storage reserves lead to smaller forward premiums, as it is a form of indirect storage. As discussed in Section 1, their intuition is largely correct but their econometric model ignores the endogeneity concerns that can bias their results. In this section, I extend their regression analysis with a more rigorous empirical specification that specifically examines the effect of natural gas capacity on the forward premium.

Before starting the regression analysis, recall that the ex-ante forward premium is the difference between the day-ahead price and the expected spot price:

$$PREM_t = FP_t - \mathbb{E}[SP_t] = FP_t - SP_t + u_t \tag{12}$$

where $PREM_t$ is the forward premium at time t, FP_t is the forward price, $\mathbb{E}[SP_t]$ is the expected spot price which is assumed equal to the actual spot price plus a random error term, u_t.

The seminal model by Bessembinder and Lemmon (2002) yields the testable hypothesis that risk premium should be increasing with skewness of the price distribution and decreasing with the variance of the distribution, when generators and retailers are risk averse. Since empirical investigations in the last decade have found mixed evidence in support of this notion (Longstaff and Wang, 2004, Douglas and Popova, 2008, Haugom and Ullrich, 2012*b*), it is worth exploring more in depth here.

The essential intuition is that the risk premium on forward contracts is lower in markets with lower ramping costs. This is because stored natural gas is equivalent to indirect storage of electricity. The lower ramping costs within new natural gas capacity should imply a greater ability to immediately convert the stored input into electricity. This increases the effectiveness of the indirect physical hedge which reduces the forward premium because the additional ramping ability potentially translates to lower price risk in the spot market.

This notion is tested empirically using a reduced form econometric specification that follows from the previous empirical literature (Longstaff and Wang, 2004, Douglas and Popova, 2008):

$$PREM_t = \beta_0 + \beta_1 NGC_t + \beta_2 VAR_{t-1} + \beta_3 SKEW_{t-1} + \beta_4 T_t + \varepsilon_t \tag{13}$$

where $PREM_t$ is the average hourly forward premium on day t, NGC_t is total natural gas capacity, VAR is variance of real-time price, $SKEW$ is the skewness of real-time price, and ε_t is a serially correlated error term such that $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$ where u_t is random noise. More specifically, a 7-day average of intra-day price variance is used for VAR as it arguably represents the best indication of ex-ante variance expectations. Similarly, a 7-day average of intra-day price skewness is used for $SKEW$. As with previous specifications, T represents a matrix of controls for time trends and includes fixed effects for month, year, and day of the week.

The regression results are presented in Table 12. As with previous analysis, Columns (A),

Table 12: Regression Results: Natural Gas & the Forward Premium
Dependent Variable: Daily Mean Forward Premium

	(A) OLS	(B) 2SLS	(C) GARCH
Natural Gas Capacity (MW)	-0.0041	-0.0125	-0.0066**
	(0.0047)	(0.0099)	(0.0030)
Variance ($/MWh)	0.0002	0.0001	0.0003
	(0.0002)	(0.0002)	(0.0007)
Skewness ($/MWh)	0.7232	0.6428	0.7548**
	(0.4984)	(0.5682)	(0.3769)
Demand (MWh)	-0.0001	-0.0012	0.0026
	(0.0032)	(0.0023)	(0.0016)
Year Fixed Effects	Yes	Yes	Yes
Observations	2313	2313	2313
Kleibergen-Paap rk-statistic		157.23	

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

(B), and (C) correspond to the pooled event study, 2SLS, and GARCH model, respectively. Across all specifications, natural gas capacity shows a small decrease in the forward premium, although this is only statistically significant in the GARCH model. The coefficients for mean demand and variance are small and insignificantly different than zero in all specifications. The marginal effect of skewness is positive and insignificantly larger in magnitude to the results in Longstaff and Wang (2004), although it is only statistically significant in the GARCH model.

Overall, the results are not considered supportive of the Bessembinder and Lemmon (2002) model and supporting literature (Longstaff and Wang, 2004, Douglas and Popova, 2008). The Bessembinder and Lemmon (2002) model suggests that the forward premium should increase with skewness and decrease with variance, but the effects shown in Table 12 are not significant. Instead, these coefficients are more supportive of recent literature by Haugom and Ullrich (2012*b*), who argue that the forward price has converged to be an unbiased predictor of the spot price in the PJM market. This appears consistent with my analysis of the ISO-NE market, which shows an average forward premium of $0.61, about 1% of the mean electricity price during my sample period.

To ensure that my results are not the result of using aggregated daily forward premiums, I also perform the regression analysis by hour. The results again control for the past week's spot price variance, spot price skewness, and mean demand. The marginal effects for natural

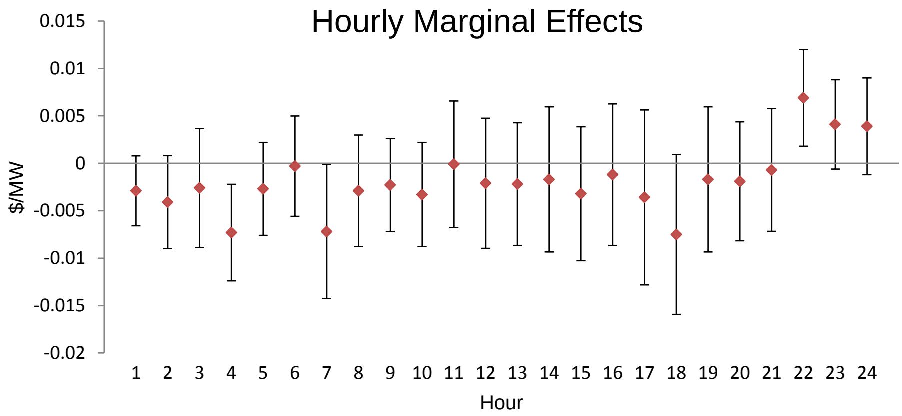

Figure 9: Hourly Marginal Effect of Natural Gas Capacity on Forward Premium

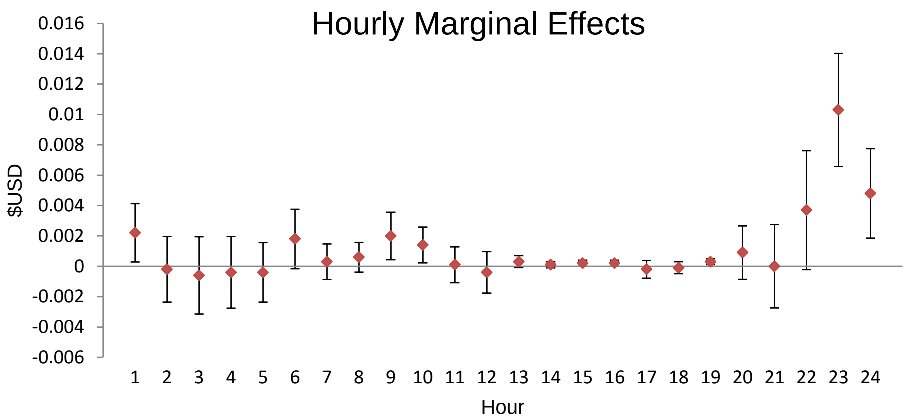

Figure 10: Hourly Marginal Effect of Variance on Forward Premium

gas capacity are shown in Figure 9. The hourly marginal effects are shown for variance and skewness in Figure 10 and 11, respectively.

The hourly marginal effects of national gas capacity on the forward premium shown in Figure 9 are consistent with the daily forward premium results of Table 12. Additional natural gas capacity routinely leads to small, insignificant reductions in the forward premium. The hourly marginal coefficients for variance and skewness are also generally insignificant but do not follow as clear of a trend. The coefficient signs and magnatudes change often, again supporting the work of Haugom and Ullrich (2012*b*) instead of the earlier literature.

A persistent forward premium implies that there is some risk premium in buying forward price contracts, such that the risk aversion of power purchasers dominates that of electricity generators. Meanwhile, in an efficient market with risk-neutral traders the forward premium should converge to zero (Jha and Wolak, 2013). Thus, I interpret these results as evidence

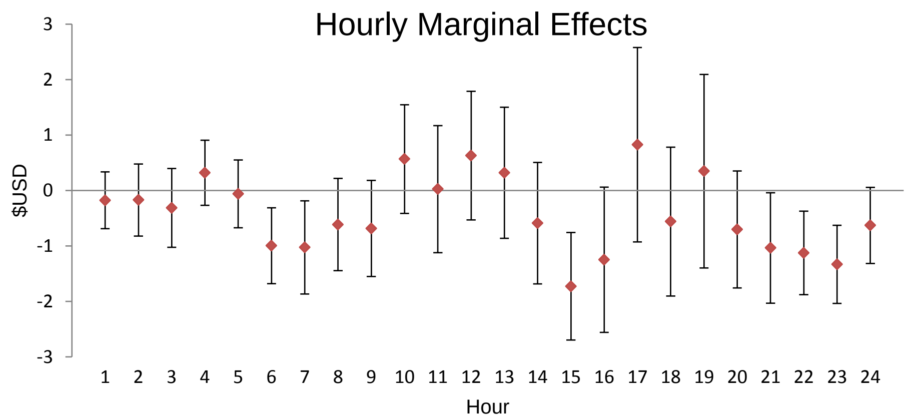

Figure 11: Hourly Marginal Effect of Skewness on Forward Premium

that the ISO-NE market is operating efficiently in the presence of sufficient risk neutral traders. While it does seem that additional natural gas capacity may slightly decrease the forward premium, this effect is not significant.

9 Conclusions

The indirect impacts of additional natural gas capacity on wholesale electricity market price behavior have not been fully analyzed in the previous literature. While natural gas capacity has obvious effects on the mean price of electricity, there is minimal discussion on the implications for price volatility. The ramping ability of natural gas plants is particularly important since there may not yet an efficient market for ramping ability within the FERC's "Standard Market Design" (Stoft, 2002, Angelidi, 2012, Wang and Hobbs, 2014). My analysis provides several contributions to the existing literature on electricity markets, as it describes and quantifies the additional benefits from adding flexible generation capacity. First, it formalizes the intuitive link between natural gas capacity and price volatility due to ramping costs. Second, it implements a rigorous empirical analysis which provides supporting evidence to the theoretical model. Finally, it builds on previous literature connecting natural gas markets and the forward premium in electricity markets, while adding to the debate over the Bessembinder and Lemmon (2002) model.

In this paper I develop a basic theoretical model which details the importance of ramping costs on electricity market price volatility. In the absence of cost-effective storage, ramping costs are a major contributor to price volatility in the electricity market. The model shows that adding generation capacity with lower ramping costs and lower marginal costs will unambiguously decrease intra-day price volatility under the standard assumptions of convexity in the cost curve. Further, the implications of the model easily generalize to all non-storable, or perishable, commodities where there are marginal costs of adjusting output. In brief, flexible production can serve a similar role to storage in ensuring price stability.

A reduced form econometric specification is inferred from the equilibrium conditions of the model and the empirical evidence supports the theory. More specifically, I find that a typical natural gas generator will reduce price volatility by approximately 5.6% in the wholesale market. These results are obtained using a high frequency data within a pooled event study regression analysis, and are robust to a two-stage least squares model and a generalized autoregressive conditional heteroskedasticity (GARCH) model. The external pecuniary benefits from the marginal natural gas generator translate to an annual gain in consumer surplus of approximately \$1.13 million due to the lower options price resulting from decreasing price volatility.

The results also show that the effect is larger during the summer months, when intra-day demand is highest and the ramping ability is most important. This suggests the important role that natural gas can play in the future, since expected growth in renewable generation is non-dispatchable and will result in larger residual demand volatilities.

The marginal effects from the econometric results are used to calibrate a simulation exploring how the option value of natural gas will change over time in the ISO-NE market as aging generators are replaced. The simulation results show that the price stability value from natural gas increases dramatically in the presence of large wind growth. Meanwhile, in the ISO-NE envisioned scenario, the price stability value of natural gas falls slowly over the next decade as natural gas growth mitigates the price volatility increases from wind production. This underscores the importance of natural gas as a compliment to non-dispatchable renewable generation because the low ramping costs of natural gas translate to corresponding price stability benefits.

The effect of natural gas capacity on the forward premium is also investigated, showing insignificant decreases to the forward premium from additional natural gas. The results are similar when using daily mean data and disaggregated hourly forward premium data. This supports recent literature suggesting the market is operating efficiently in the presence of sufficient risk neutral traders, resulting the forward price converging to an unbiased predictor of the spot price.

Taken together, the results of this analysis point electricity market regulators towards specific policies. First, market design and policies should acknowledge that there are additional benefits around adding capacity that has both low ramping costs and low marginal costs, such as natural gas generators. This is increasingly important when considering the future growth of non-dispatchable generators such as wind and solar. Since the benefits around ramping costs may not be properly priced under the current design of most electricity markets, incentives must be created to ensure such benefits are internalized into long-run capital investment decisions. This can be done through an additional market for ramping services, as several transmission organizations have begun to create. In the meantime, construction subsidies may be offered to ensure additional investment in flexible generators. Incentive-based support mechanisms should remain in place until cost-effective storage reduces ramping issues to irrelevance.

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