The impact of wind generation on the electricity spot-market price level and variance:

the Texas experience

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Abstract

The literature on renewable energy suggests that an increase in intermittent wind generation would reduce the spot electricity market price by displacing high fuel-cost marginal generation. Taking advantage of a large file of Texas-based 15-min data, we show that while rising wind generation does indeed tend to reduce the *level* of spot prices, it is also likely to enlarge the spot-price *variance*. The key policy implication is that increasing use of price risk management should accompany expanded deployment of wind generation.

Keywords: wind energy, electricity price, risk management

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1. Introduction

The existing literature on renewable energy suggests that an increase in intermittent wind generation offers two financial benefits. In the context of a competitive generation market, the benefit is a reduction in spot electricity prices due to the increase in wind generation displacing marginal generation with a high fuel cost (EWEA, 2009, 2010; Woo et al., 2011a; Sensfuß et al., 2008). From the perspective of electricity consumers, this benefit can be large, since the price reduction would apply to all of the spot-market purchases made directly by themselves or on their behalf by a local distribution company.¹ In the context of an integrated utility, the benefit is that the increase in wind generation cuts the utility's natural-gas purchase cost and provides a hedge against the fuel-price risk (Bolinger et al., 2005; Berry, 2005). Such benefits, however, may come at the cost of an increase in the spot-price variance (Milstein and Tishler, 2011; Chao, 2011; Jacobsen and Zvingilaite, 2010; Green and Vasilakos, 2010).

There is extensive research on spot electricity price behavior and dynamics (e.g. Woo et al., 2011b and the references therein). There is, however, only limited evidence based on actual market-price data enabling one to study the impact of rising wind generation on spot electricity prices. Such a study is particularly salient at this time because wind generation is the primary and abundant source of renewable energy now being promoted by government policies in many parts of the world, including North America, Europe and China (Woo et al., 2011a; Lu et al., 2009; Hoogwijka et al., 2004). If rising wind generation has a large impact on the variance of spot-market prices, then expansion of wind-generation capacity should also be accompanied by an increasing use

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of electricity price risk-management instruments and techniques (e.g., Deng and Oren, 2006; Eydeland and Wolyniec, 2003).

The purpose of this paper is to conduct that salient study by estimating the parameters of a partial-adjustment linear regression model of spot electricity (i.e., balancing energy) prices in Texas. The estimated model enables a direct prediction of the effect of an increase in wind generation on spot electricity price level and variance, which provides important information useful for making electricity procurement and risk-management decisions (e.g., Woo et al., 2004a, 2004b, 2006).

The Texas experience is important because of the state's large and rising wind generation, and because Texas is the largest electricity-consuming state in the nation. And to the best of our knowledge, there is only one econometric analysis of high-frequency market-price data, such as we employ, directed at the impact of wind generation on spot electricity prices.² Nicholson et al. (2010, p.19) find that a 100-MWH increase in wind generation in Texas may reduce the four-zone Electricity Reliability Council of Texas (ERCOT) 15-min balancing-energy market price by \$0.71/MWH in the Houston zone, \$0.07/MWH in the North zone, \$0.57/MWH in the South zone, and \$1.18/MWH in the West zone where nearly all wind generation resides. What is not known is what the same 100-MWH may do to the ERCOT's zonal price variance.

We take advantage of a unique and rich ERCOT data base fully described in Woo et al. (2011b). The data comprise 15-min electricity prices in each of the four ERCOT zones, observed over the 41-month period of January 2007 through May 2010. Seldom available elsewhere, this database has four distinct features that aid our detection of the

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price effects of wind generation (Sioshansi and Hurlbut, 2010; Woo et al., 2011b; Zarnikau, 2011):

- The installed capacity of wind generation grew during the 11-year period of 1999 to 2009 from less than 500 MW to over 7,500 MW, and now accounts for about 10% of ERCOT's total generation capacity of approximately 80,000 MW. When combined with the intermittence of wind generation, this feature leads to widely dispersed levels of wind-energy output, a requisite for statistically precise detection of its effect on market prices.
- Wind generators have a tax-credit incentive to make very low, even negative supply bids, so as to be treated as must-run and dispatched by the ERCOT independent system operator. This feature helps unmask the price effects of wind generation, not confounded by the generators' bidding behaviors.
- ERCOT's marginal generation in the non-West zones is likely to be natural-gas fired and dispatchable, offering ample opportunity for spot-price reductions through its displacement by wind generation. If the marginal generation were must-run and nondispatchable (e.g., nuclear or run-of-river hydro), wind generation might not have a detectable price effect because the marginal supply bid and the resulting marketclearing price would have been close to zero.
- ERCOT's 15-min zonal loads are price-insensitive and therefore can be used as exogenous variables to delineate market price movements due to fluctuating demands (ERCOT, 2004). This feature leads us to suggest that a detected price effect of wind generation could not have been biased by the possible price response of zonal loads.

As will be shown, the ERCOT data base enables us to confirm that while rising wind generation tends to reduce the *level* of spot prices, it also tends to enlarge the spotprice *variance*. The key policy implication is that increasing effort in price risk management should accompany expanded deployment of wind generation.

2. Model

The focus of our attention is the 15-min balancing-energy market price within each of the four ERCOT zonal markets. Suppressing a subscript to delineate the individual zones, let Y_t denote that zonal market price in a particular zone during time interval *t*. The price Y_t , which is the dependent variable in a linear regression model with partial adjustment, is driven by a set of seven numeric metric variables, denoted x_{rt} (r =1,...,7), the lagged price, Y_{t-1} , which gives the model its partial-adjustment character, and a set of three time-dependent binary indicators that account for month of the year (M_{it}), day of the week (W_{jt}), and hour of the day (H_{kt}), with i = 1, ..., 11; j = 1, ..., 6; k = 1, ...,23. Letting ϵ_i denote a normally-distributed disturbance term, the model is written as:

$$Y_t = \alpha + \sum_r \beta_r x_{rt} + \gamma Y_{t-1} + \sum_i \mu_i M_{it} + \sum_j \omega_j W_{jt} + \sum_k \eta_k H_{kt} + \varepsilon_t.$$
(1)

In equation (1), ε_t is assumed to follow a stationary AR(1) process: $\varepsilon_t = \rho \varepsilon_{t-1} + \upsilon_t$, with $|\rho| < 1$ and υ_t = white noise (Kmenta, 1984, pp.528-536). The coefficients to be estimated are α , { β_r }, γ , { μ_i }, { ω_i }, { η_k } and ρ .

Four sets of coefficients are estimated, one for each ERCOT zone, based on samples of approximately 116,000 observations. As will be seen, our AR(1) assumption is validated for all four regressions. The estimated model will ultimately be used to explore the impact of changes in wind generation on the levels and variances of the zonal market prices.

The seven metric variables are as follows:

- x_{1t} is the 15-min wind generation of the ERCOT system, which is largely at the mercy of random wind conditions. We hypothesize that rising wind generation reduces market price, which translates into the hypothesis: $\beta_1 < 0$.
- x_{2t} is the 15-min MWh nuclear generation in the ERCOT system. We do not use the 15-min data on dispatchable generation (i.e., hydro, coal, and natural gas), because they are endogenous as a result of ERCOT's least-cost dispatch decisions (ERCOT, 2004). Nuclear generation is baseload and non-dispatchable. Reducing nuclear output due to maintenance, repair or refuel is expected to raise the market price. This translates into the hypothesis: β₂ < 0.
- x_{3t} is the daily Henry Hub natural-gas price. Because of Texas's vast thermalgeneration fleet, we use the exogenous Henry Hub price, which is almost perfectly correlated with the Houston Ship Channel price (R = 0.99), to quantify what we hypothesize to be the positive price effect of the marginal fuel (natural gas) on the electricity market price. This translates into the hypothesis: $\beta_3 > 0$.
- x_{4t}, x_{5t}, x_{6t}, x_{7t} are 15-min exogenous MWh loads in ERCOT's Houston zone, North zone, South zone, and West zone, respectively. Rising loads tend to raise market prices; hence, (β₄, ..., β₇) are hypothesized to be positive.
- An increase in the lagged price likely raises the current price, with its effect dampening over time (Woo et al., 2007). This translates into the hypothesis: 0 < γ < 1. The size of γ measures the speed of adjustment such that 1/(1 γ) is the number

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of 15-min intervals required to achieve the equilibrium state of $Y_t = Y_{t-1}$, implying $\beta \equiv \beta_1/(1 - \gamma)$ is the "full" price effect of wind generation.

The binary indicators aim to capture the spot price's residual time-dependence that may exist *after* controlling for the influence of the aforementioned metric variables. They are: (a) $M_{it} = 1$ for i = 1 (January), ..., 11 (November), and is zero otherwise; (b) $W_{jt} = 1$ for j = 1 (Sunday),..., 6 (Friday), and is zero otherwise; and (c) $H_{kt} = 1$ for k = 1 (an hour ending at 1:00), ..., 23 (an hour ending at 23:00), and is zero otherwise.

3. Data

Table 1 presents the descriptive statistics for the approximately 116,000 observations used in our regression analysis. It shows that 15-min zonal prices are highly volatile, have large spikes (e.g., up to \$4500/MWH for the North zone), and can be negative (e.g., -\$1,536/MWH for the Houston zone). Reflecting capacity growth and output intermittency, the 15-min wind-generation output has a range of zero to 1,703 MWH, with an average of 444 MWH. The 15-min nuclear generation tends to be close to full capacity, as evidenced by the average output of 1,159 MWH and maximum output of 1298 MWH. The daily Henry Hub natural-gas-price data has a wide range of \$1.8 to \$13.3/MMBTU, with an average of \$6.4/MWH. Finally, the 15-min zonal loads are volatile with large spikes. For example, the North zone's maximum load of 6555 MWH is almost twice the average load of 3357 MWH).

		Standard		
Variable	Mean	deviation	Minimum	Maximum
15-min Houston zone price				
(\$/MWH)	50.9	95.4	-1536.0	3806.0
15-min North zone price				
(\$/MWH)	47.2	73.2	-999.0	2383.0
15-min South zone price				
(\$/MWH)	51.0	110.1	-2293.0	4515.0
15-min West zone price				
(\$/MWH)	42.5	77.7	-1982.0	2321.0
15-min wind generation				
output (MWH)	444.7	339.1	0.0	1703.0
15-min nuclear output				
(MWH)	1159.0	201.6	0.0	1298.0
Daily Henry Hub natural gas				
price (\$/MMBTU)	6.4	2.4	1.8	13.3
15-min Houston zone load				
(MWH)	2413.0	558.4	1278.0	4416.0
15-min North zone load				
(MWH)	3397.0	859.2	1714.0	6555.0
15-min South zone load				
(MWH)	2379.0	589.3	1344.0	4491.0
15-min West zone load				
(MWH)	589.0	99.1	382.7	974.1

Table 1: Descriptive statistics for the sample period of January 2007 to May 2010.

Note: The Phillips-Perron unit-root test results indicate that all zonal market prices are stationary, thus obviating our concern of spurious regressions (Davidson and MacKinnon, 1993, Chapter 19).

Figures 1-4 are scatter plots to presage the effects of wind generation on zonal

market prices. They indicate statistically-significant ($\alpha \leq 0.01$) negative but weak

correlations (-0.0842 > R > -0.2336) between wind generation and prices. For the non-

West zones, the price dispersion does not seem to depend on wind generation. For the

West zone, it seems to diminish with wind generation.



Figure 1: ERCOT wind generation vs. Houston zonal price for the sample period of January 2007 to May 2010.



Figure 2: ERCOT wind generation vs. North zonal price for the sample period of January 2007 to May 2010.



Figure 3: ERCOT wind generation vs. South zonal price for the sample period of January 2007 to May 2010.



Figure 4: ERCOT wind generation vs. West zonal price for the sample period of January 2007 to May 2010.

While these figures hint at the effect of an increase in wind generation on the spot-price level and variance, they do not paint a clear picture of what that effect may be because of other influencing factors (e.g., zonal load variations) not captured in the figures. As a result, our identification and estimation of rising wind generation's price effect will come from the zonal market-price regressions reported in the next section.

4 **Results**

4.1 Zonal market-price regressions

Table 2 presents the maximum likelihood estimates of equation (1) for each of the four zones. For a very large sample size of $N \approx 116,000$, each regression's $R^2 \approx 0.4$ suggests a quite credible fit to the data, given the substantial amount of noise resulting from the high frequency of the observations. Although smaller than the standard deviations for zonal spot prices in Table 1, the root-mean-squared-errors (RMSE) remain large, ranging from \$60/MWH to \$80/MWH.

Table 2: Zonal market-price regression results obtained by applying the method of maximum likelihood. For brevity, this table does not report the coefficient estimates for the intercept and binary indicators that indicate statistically-significant time-dependence of the 15-min market prices ($\alpha \le 0.01$). Values in () are standard errors of the coefficient estimates and "*" denotes "significant at the 1% level".

Variable: coefficient	Dependent variable: Zonal market price			
	Houston	North	South	West
Total R^2	0.41	0.34	0.46	0.40
Mean squared error: MSE	5345	3543	6492	3609
Root mean squared error:	73.1	59.5	80.6	60.1
RMSE				
15-min wind generation	-0.0039*	-0.0061*	-0.0032*	-0.0153*
output (MWH): β_1	(0.0006)	(0.0005)	(0.0006)	(0.0005)
15-min nuclear output	-0.0057*	-0.0048*	-0.0047*	-0.0070*
(MWH): β_2	(0.0011)	(0.0010)	(0.0013)	(0.0010)
Daily Henry Hub natural	1.8999*	1.8217*	1.5985*	1.0731*
gas price ($/MMBTU$): β_3	(0.1065)	(0.0913)	(0.1169)	(0.0956)
15-min Houston zone load	0.0097*	0.0072*	0.0090*	0.0053*
(MWH): β_4	(0.0011)	(0.0009)	(0.0012)	(0.0010)
15-min North zone load	0.0017	0.0055*	0.0008	0.0045*
(MWH): <i>β</i> ₅	(0.0008)	(0.0007)	(0.0009)	(0.0007)
15-min South zone load	0.0039*	-0.0008	0.0046*	-0.0001
(MWH): β_6	(0.0011)	(0.0009)	(0.0012)	(0.0010)
15-min West zone load	0.0250*	0.0252*	0.0252*	0.0225*
(MWH): <i>β</i> ₇	(0.0050)	(0.0043)	(0.0056)	(0.0046)
Lagged 15-min price	0.7113*	0.6221*	0.7540*	0.6527*
(\$/MWH): γ	(0.0025)	(0.0031)	(0.0023)	(0.0030)
	-0.2649*	-0.2030*	-0.2651*	-0.1492*
AR(1) parameter: ρ	(0.0034)	(0.0039)	(0.0033)	(0.0040)

The coefficient estimates in Table 2 are conditional on the *lagged* 15-min price and lead to the following observations:

The statistically-significant estimates for β₁ indicate that 100-MWH increase in wind generation reduces market price by 100 x 0.0039 = \$0.39/MWH in the Houston zone, \$0.61/MWH in the North zone, \$0.32/MWH in the South zone, and \$1.53/MWH in the West zone, thus corroborating the price effects found by Nicholson et al. (2010), and supporting our first hypothesis.

- The statistically-significant estimates for β₂ indicate that a 1000-MWH drop in nuclear-generation output can cause the zonal prices to increase by \$5/MWH to \$7/MWH (e.g., 1000 x 0.0070 in the West zone), and support our second hypothesis.
- The statistically-significant estimates for β_3 indicate that a \$1/MMBTU increase in the price of natural gas leads to a \$1/MWH to \$2/MWH zonal price increase, and support our third hypothesis.
- The statistically-significant estimates for β₄ to β₇ support our fourth hypothesis that rising zonal loads tend to raise zonal market prices. Their price effects, however, are uneven. A 100-MWH load increase in non-West zones has less than a \$1/MWH effect. In contrast, the same 100-MWH load increase in the West zone may reduce zonal prices by as much as \$2.5/MWH.
- The statistically-significant estimates for γ support our fifth hypothesis, indicating that a \$1/MWH change in the lagged price can raise the subsequent price by \$0.62/MWH to \$0.75/MWH. As 1/(1 γ) measures the speed of adjustment, a range of 0.62 to 0.75 for the γ estimates implies that the zonal prices can rapidly adjust to their equilibrium state within one hour (i.e., three to four 15-min intervals).
- The statistically-significant estimates for p are between -0.15 to -0.26, indicating that the zonal price series have moderate first-order negative autocorrelation and affirm the validity of our AR(1) assumption. Thus, a past random shock would have an oscillating and dampening effect on the current prices.

4.2 Cross-hedging

A useful application of the estimates for β_3 and γ in Table 2 is to find the minimum-variance (MV) hedge ratio of $\beta_3/(1 - \gamma)$ MMBTU per MWH for using NYMEX monthly natural-gas futures to cross-hedge against the effect of natural-gas price volatility on spot electricity price volatility (Woo et al., 2011c). The hedge-ratio estimates thus found are (a) Houston zone: 6.58; (b) North zone: 4.82; (c) South zone: 6.50; and (d) West zone: 3.09. Because the West zone has nearly all of the state's wind generation, we infer that rising wind generation tends to reduce the MV cross-hedge ratios.

4.3 Some additional considerations

Before engaging in our exploration of the impacts of changes in wind generation, we take a minor detour into some additional modeling considerations.

Although a double-log specification would better characterize the skewed spotprice distributions, the presence of negative prices prevents us from using that ostensibly desirable alternative to our linear model.

We do, however, test for whether the daytime (07:00 - 19:00) price effect of wind generation differs from its nighttime (19:00 - 07:00) price effect. We do so by reestimating the four regressions after adding an interaction explanatory variable formed by the nighttime binary indicator multiplied by the wind-generation variable. The *t*-statistics for the coefficient estimates for this additional variable show that it is not statistically significant ($\alpha = 0.01$), Hence, we fail to reject the hypothesis that the daytime and nighttime price effects are equal. We also re-estimated the price regressions assuming an AR(2) process for ε_{l} . The resulting estimates for β_{1} to β_{7} and γ are not materially different from those in Table 2, and are not reported here.

Finally, we re-estimated the price regressions after making alternative assumptions regarding the error term's stochastic process: AR(1)/GARCH(1, 1), GARCH(1, 1), AR(1)/ARCH(1), and ARCH(1) (Alexander, 2001, Chapter 4). The estimated processes are non-stationary. Moreover, the new regressions show a statistically-significant ($\alpha = 0.01$) but counter-intuitive result that rising nuclear generation tends to *raise* market prices. Hence, we conclude that these assumptions are inappropriate for quantifying the price effects of an increase in wind generation.

5 Predicting the price effects of rising wind generation in Texas

The second row of Table 3 reports the estimates of $\beta \equiv \beta_1/(1 - \gamma)$ by zonal market. These estimates indicate that the "full" effect of a 100-MWH increase in wind generation are price reductions of 100 x 0.0137 \approx \$1.4/MWH in the Houston zone, \$1.6/MWH in the North zone, \$1.3/MWH in the South zone, and \$4.4/MWH in the West zone.

Table 3: The zonal price effects of a 10% increase in wind generation's installed capacity in Texas. Values in () are standard errors of the coefficient estimates for $\beta \equiv \beta_1/(1 - \gamma)$ and "*" denotes "significant at the 1% level". The price and wind-generation output means and variances are based on the 15-min data in the 12-month period of June 2009 -May 2010. The mean for wind generation is G = 600.5 MWH and variance V = 155,946MWH.

	Zonal market				
Variable	Houston	North	South	West	
Estimates of $\beta \equiv \beta_1 / (1$	-0.0137*	-0.0162*	-0.0128*	-0.0441*	
- 7)	(0.0019)	(0.0013)	(0.0025)	(0.0015)	
Price mean	35.1	33.1	36.2	29.7	
Price standard					
deviation	63.7	39.1	89.8	34.5	
Price variance	4057.7	1528.8	8064.0	1190.3	
Price change	-0.82	-0.97	-0.77	-2.65	
Price change as					
percent of price mean	-2.34	-2.94	-2.12	-8.91	
Price variance change	6.5	8.8	6.0	63.8	
Price variance change					
as percent of price					
variance	0.16	0.57	0.07	5.36	

Note: The standard errors in () are found by a Taylor series approximation (Mood et al., 1974, p.181).

We use the following easily implemented five-step process to predict the spot price effects triggered by a 10% increase in the installed capacity of wind generation in Texas:

- Step 1: Compute the mean and variance of the 15-min price and wind data for the most recent 12 months in our data base, which are June 2009 through May 2010.
- Step 2: Assume a scalar φ > 1 so that 100(φ 1) is the percent increase in wind generation's installed capacity (e.g., φ = 1.1 implies a 10% increase in installed capacity). For the period of June 2009 through May 2010, the mean generation over all 15-min intervals is G = 600.5 MWH. Thus, a projected 10% increase in the mean wind generation is (φ 1)G = 0.1 x 600.5 = 60.05 MWH.

- Step 3: Compute the variance of wind generation after the capacity addition. Thus, in the present instance the original variance is V = 155,946 MWH and the new variance is $\phi^2 V = 1.21 \ge 155,946 = 188,695$ MWH.
- Step 4: Compute the price change given by b(φ 1)G, where b is the estimate of β in the second row of Table 3. Focusing on the Houston zone, the price change is given by -0.0137 x 0.1 x 600.5 = -0.82, as shown the sixth row of Table 3.
- Step 5: Apply the forecast variance formula in Feldstein (1971, p.56) to predict the change in the spot price variance. Under the assumption that wind generation is statistically independent of other drivers in the spot price regressions, the predicted variance change is (\$\varphi^2 1\$) [\$G^2\$ var(b) + b^2\$ V + var(b) V], where var(b) = variance of b.³ For Houston, var(b) is (-0.0019)² = 0.00000361; and the predicted change in variance is 0.21 x [360,600.3 x 0.00000361 + 0.00018769 x 155,946 + 0.00000361 x 155,946] = 6.5, as shown in the eighth row of Table 3.

Table 3 thus shows the price effects of a 10% increase in the installed capacity of wind generation by zonal market. The computations confirm the commonly postulated price reductions, which range from 2% in the non-West zones to almost 9% in the West zone. They also show increases in the price variance of less than 1% in the non-West zones and about 5% in the West zone. Hence, the price effects of increasing wind generation tend to be relatively small in the non-West zones and relatively large in the West zone.

6. Conclusions

Using the large ERCOT data base, we estimate four zonal price regressions to confirm that while increases in wind generation tend to reduce the level of electricity spot prices they also tend to enlarge the spot-price variance. Thus, as more wind-generation capacity is installed in an electrical system and utilities increasingly rely on wind generation, that increasing reliance would have serious implications for both expected electricity spot prices *and* their variances. Policy makers and market agents, as well as consumers, will welcome the prospect of lower prices, and many environmentalists will likely support the increasing reliance on this price-reducing source of renewable energy. These benefits, however, are accompanied by an additional challenge for policy makers and utility managers: notably, dealing with the increased price risk implied by the increased price variance that is inseparable from increased reliance on what is an inherently intermittent source of generation.

To meet that challenge, the principal actors will need to expend increased effort in risk management and become increasingly familiar, in particular, with the financial instruments that have proved their worth in the financial sector. The expectation, in this context at least, is that familiarity will breed increasing comfort with using those instruments to the ultimate benefit of consumers.

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Endnotes

¹ The spot price decline, however, could discourage investment in thermal generation (Traber and Kemfert, 2011; Steggals et al., 2011), which might in turn cause spot price spikes during hours of low wind generation (Milstein and Tishler, 2011).

² This is based on our literature search done at scholar.google.com on January 22 2011, using the following keywords: "spot electricity", "price volatility", "wind energy". ³ This assumption reflects our view that rising wind generation should not have any effect on nuclear generation and Henry Hub natural-gas prices. While wind generation and zonal loads are negatively correlated, we decided not to include this correlation in our computation for the following reasons. First, the correlation is weak, with *R* between -0.15 to -0.22 for the period of June 2007 – May 2010. Second, its inclusion would only magnify our estimated change in variance. This is because a random increase in wind generation, when coupled with correlated decreases in zonal loads, would enlarge the price reduction due to the wind generation increase alone. Finally, its inclusion vastly complicates the computation (see Feldstein, 1971, p.56, equation (4)). Although this additional complication is manageable, it makes the process somewhat less "easily implemented" and detracts from the exposition, without adding materially to our understanding of the fundamental issues at hand.