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Abstract

This paper provides some evidence on electricity–natural gas price interactions along with trade effects on electricity prices. The analysis helps to better understand integrated electricity markets, notably to test if expected market outcomes are actually obtained. Our contribution is therefore to provide an applied econometric modeling approach, and a real illustration, to establish to what extent natural gas prices influence electricity prices and if imports reduce electricity prices. To study such issues, we consider the case of the Ontario electricity market where natural gas plants are the marginal plants only during periods of extremely high demand. Our analysis of this market suggests that natural gas prices do have an impact on electricity prices. In addition, if imports are expected to reduce electricity prices, our results suggest the opposite when we use daily data, as already found in the literature. However, when hourly data are used, electricity imports are found to have a negative effect on price.

Key Words: Natural gas effect; Role of imports; Time series models; Granger causality.

Résumé

Cet article étudie la relation entre le prix de l'électricité et celui du gaz naturel conjointement avec l'effet des importations d'électricité. L'analyse aide à comprendre mieux les marchés intégrés de l'électricité, pour examiner notamment si des résultats prévus du marché sont obtenus réellement. Notre contribution est donc de fournir un modèle économétrique, appliqué sur un vrai marché, pour établir dans quelle mesure le prix du gaz naturel et les importations influencent le prix de l'électricité. Pour étudier de telles questions, nous considérons le cas du marché de l'électricité d'Ontario où les usines de gaz naturel sont des usines fonctionnant seulement pendant des périodes où la demande est extrêmement élevée. Notre analyse de ce marché suggère que le prix du gaz naturel a un impact sur le prix de l'électricité. De plus, si on s'attend à ce que les importations réduisent le prix de l'électricité, nos résultats suggèrent l'opposé quand nous employons des données quotidiennes, comme déjà rapporté dans la littérature. Cependant, quand des données horaires sont employées, les importations de l'électricité s'avèrent avoir un effet négatif sur le prix.

Mots clés : Effet du gaz naturel; Rôle des importations; Modèles de séries chronologiques; Causalité au sens de Granger.

1 Introduction

The deregulation of electricity markets was implemented to various degrees in many countries over the world. In 1982, Chile was the first country to experience the transition from the former to the current electricity sector. Afterward, different countries have followed a similar framework such as Australia, Spain, England, and some states in the US. The usual objective of such reforms is to introduce a competitive market with the expectation that better price and investment signals will improve market efficiency. A side effect of the deregulation process is to increase electricity price volatility, as a consequence of many factors. Some of those factors are demand fluctuations, operating reserves, transmission capacity, temperature, fuel prices and power import (Angelus, 2001). In this paper we further examine the contribution of natural gas and trade on the price formation process. Accordingly, we investigate whether natural gas has any impact on electricity price and if imports are driven by arbitrage opportunities, and hence decreasing the local electricity price. In particular, we study these issues via the Ontario market.

Natural gas is playing an important role in electricity markets for at least two reasons: environmental concerns and technology. Indeed, policies aimed at reducing CO_2 emissions are giving natural gas the position of a transition fuel to a less polluting economy. Besides, small efficient natural gas plants can be built with relatively low investment capital and within two years, while coal and nuclear power take years just to get an official approval. Factors which may foster further use of natural gas for electricity production are the development of an international market for liquefied natural gas (LNG), the increasing production of shale gas, access to stranded reserves (becoming technologically and economically recoverable) and possibilities of intercontinental arbitrage.

Electricity trading activities have also increased tremendously, following the evolution of power markets from vertically integrated monopoly structures to ones marked by the unbundled functions of generation, distribution and transmission. Different market structures have emerged, including pools, Over the Counter (OTC) bilateral trade and organized futures exchanges. Such markets aim at ensuring production at minimum costs and are useful because of price differentials within and between regions, arising because of different technologies, non-simultaneous peak demands and diverging regulatory rules.

In Ontario, different laws have been adopted to transform the electricity market since 1996. One of the outcomes of such transformation is the increase in price volatility. Indeed, Ontario market prices are claimed to be among the most volatile over the world (Zareipour et al., 2007). Such volatility can be attributed to different factors such, weather and fuel prices. While coal is the marginal fuel most of the time in Ontario, it is very likely that its share in the supply mix will decline in favor of less polluting energy sources such as renewable energy and natural gas. Indeed, it was planned that coal power plants would be retired in 2007 but such an initiative was postponed to 2014 (Hrab and Fraser, 2009). It was noticed also that natural gas plants are the marginal plants only during periods of extremely high demands (Zareipour et al., 2007).

Ontario is connected to five other control areas: Quebec, Manitoba, New York, Michigan and Minnesota. Between 2006 and 2009, Ontario has been a net exporter. Therefore, one would expect that Ontario is importing electricity only if such imports are less expensive than local production, and hence having a lowering impact on the electricity prices.

The remaining of the article is as follows: Section 2 is a description of Ontario electricity market, Section 3 is summary of the daily data and the results of the gas effect on electricity prices, Section 4 is summary of the hourly data and the results of how imports volumes are related to power prices and Section 5 concludes.

2 Our Example: The Ontario Electricity System

Until the mid 1990s, Ontario Hydro was the main integrated electricity company (in generation and transmission), responsible for both planning and operating the Ontario power system. Since 1998, different laws such as the Competition Electricity Acts have been passed. They aimed at developing competitive wholesale and retail markets, ending Ontario Hydro integrated activities and giving birth to different firms responsible for unbundled activities. In 2004, however, the Electricity Restructuring Act was enacted and the Ontario

Power Authority (OPA) was created to take charge of power planning and long-term electricity procurement, along with facilitating the establishment of a competitive electricity market. This in fact re-introduced some regulation and as consequence, a hybrid electricity system emerged where a competitive market is operating along with regulated prices in parts of the system. Indeed, the competitive market consists of metered market participants and wholesale customers who pay the Hourly Spot Market Price (HOEP) while the regulated prices (by OPA) are used for the low volume and designated consumers. On the supply side, as of 2010, Ontario's installed capacity is 35,781 MW distributed by technology as in Figure 1.

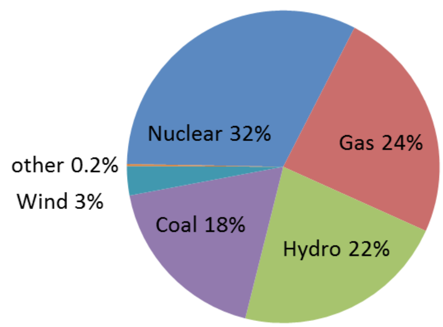

Figure 1: Ontario installed capacity (IESO, 2010)

In terms of market operations, Ontario is organized as a single market clearing price auction. Suppliers submit offers to sell energy and they receive a market clearing price which is calculated every five minutes. The average of these five minute clearing prices across the hour is the hourly Ontario electricity price (HOEP). The market operator provides the markets participants with a three-hour ahead pre-dispatch schedule summarizing the latest information on supply and demand before submitting their bids.

Ontario is connected to five other control areas/markets: Quebec, Manitoba, New York, Michigan and Minnesota. From 2006 to 2009, Ontario has been a net exporter (Figure 2). Approximately 80% of exports from Ontario go to New York. Mainly for reliability reasons, importers of electricity into Ontario receive their offers' prices even if they are higher than spot prices while electricity exporters do not have such a protection (Peerbocus and Melino, 2007).

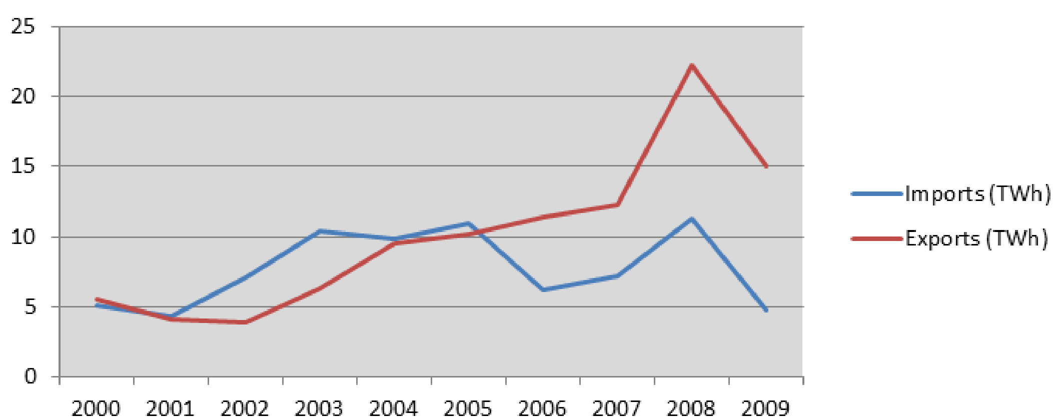

Figure 2: Ontario import and export (IESO, 2010)

3 Gas Effect

Using the "Dawn-Index" as a proxy for natural gas prices, Arciniegas Rueda and Marathe (2005) show that the natural gas is important in explaining electricity prices in the Ontario market but not as important as other factors such as imports. They postulate, however, that this could be due to the fact that a large share of the gas used for power generation is procured on a long term basis. The Dawn Hub is the second most liquid natural gas trading center in Canada with a storage capacity of Union Gas' Dawn Hub of around 155 Billion cubic feet (Bcf) and the ability to inject or withdraw around 2.8 Bcf at peak. In this section we use the Henry Hub Futures instead, we find that there is a presence of gas effect on electricity prices; in our ARMAX model, the gas variable is statistically significant and its effect is more important than imports'. Furthermore, the sensitivity of the electricity prices to changes in gas prices captured in the data is around 7.7 $CAN/Mwh per 1 $US/MMbtu, which is close to what would be expected from a cost "pass through" perspective (around (7 to 10 $CAN/Mwh) per (1 $US/MMbtu)). Indeed, for gas plants with a heat rate in the 7,000-10,000btu/Kwh range, an increase of gas prices of one dollar will induce an additional cost around 7 to 10 $CAN/Mwh. Such results suggest that the gas price variability is transferred to electricity prices on a short term basis, which is supported by the fact that the gas price volatility (Granger) causes electricity prices volatility, as we show in the next sections.

3.1 Description of data and variables

Our data set was obtained by merging three databases coming from the IESO (ISEO, 2010), Environment Canada (EC, 2010) and EIA (EIA, 2010a). The explanatory variables are chosen as per Rueda and Marathe (2005). We use the import volumes, Ontario temperature and natural gas price. The data collected span from May 1$^{\text{st}}$ 2003 to October 20$^{\text{th}}$ 2009, excluding weekends and public holydays. In total, our raw data thus contain 1,624 daily observations. Table 1 reports the summary statistics for each of these variables:

1. The daily electricity Peak price (Spikes) is the dependent variable ($CAN/MWh). It is measured as the maximum price of HOEP over the weekday i; $\text{Spikes}_i = \text{MAX}_{j=1,..,24}(\text{HOEP}_{ij})$
2. The Ontario temperature (Tempm) (°C). To capture the temperature variability in the Ontario district, the average of Toronto, Ottawa, Windsor and Sudbury hourly temperatures is calculated. In order to use a daily temperature we apply the average over the weekday. It is common to use the variables HDD (heating degree-days) and CDD (cooling degree-days), with 21°C as the base temperature, instead of the actual values of temperature. The variables HDD and CDD are calculated as follow:

$$\text{HDD} = \begin{cases} 21 - \text{Tempm}, & \text{Tempm} < 21 \\ 0, & \text{otherwise} \end{cases}$$

$$\text{CDD} = \begin{cases} \text{Tempm} - 21, & \text{Tempm} > 21 \\ 0, & \text{otherwise} \end{cases}$$

3. The import volumes (Importsm) (MW) calculated as the average of hourly import volumes over the weekday.
4. The natural gas price (Gasprice) ($US/MBTU) is the Henry Hub price.

Table 1: Summary statistics of the variables from May 1$^{\text{st}}$ 2003 to October 20$^{\text{th}}$ 2009 ($n = 1,624$)

Variables	Min	25%-quantile	Median	75%-quantile	Max	Mean	Std.Dev.
Spikes	19.29	68.83	86.22	109.74	699.65	98.13	59.23
Gasprice	2.51	5.59	6.70	7.69	15.38	6.95	2.26
Importsm	0.00	567.53	950.98	1348.81	2891.83	988.53	516.99
HDD	0.00	2.71	11.18	21.14	43.14	12.69	10.65
CDD	0.00	0.00	0.00	0.00	8.58	0.26	0.91

3.2 ARMAX model

A logarithmic transformation of the data was used because of right skewness. Figure 3 displays the sample distribution of the dependent variable Spikes and its logarithmic transformation (log (Spikes)). An augmented

Dickey-Fuller test (ADF), (Dickey and Fuller, 1979), confirms the stationarity of the time series log (Spikes) (ADF t-test (calculated) = -5.12 < ADF t-test (observed) = -2.86 at the 5% level). Further examination of the autocorrelation and partial autocorrelation functions of the stationary time series log (Spikes) combined with the use of information criterions AIC (Akaike, 1974) and SBC (Schwartz, 1978) indicated the following ARMAX specification:[1]

$$\begin{aligned} \log(\text{Spikes})_t \quad = \quad & \beta_0 + \beta_1 * \log(\text{Spikes})_{t-1} + \beta_2 * \log(\text{Spikes})_{t-2} + \\ & \phi_1 * \text{Gasprice}_t + \phi_2 * \text{Importsm}_t + \phi_3 * \text{HDD}_t + \phi_4 * \text{CDD}_t + \\ & \theta_1 * \varepsilon_{t-1} + \varepsilon_t \end{aligned} \tag{1}$$

where β_0 is the intercept, β_i are the coefficients of the two autoregressive terms, ϕ_i are the coefficients of the four explanatory variables, θ_i is the coefficient for the moving average terms and ε_t is the error term.

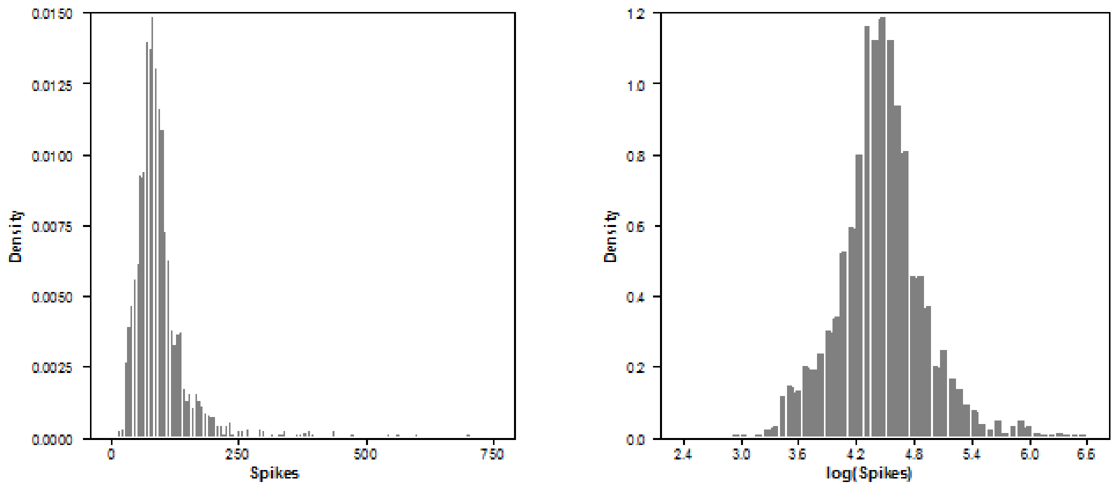

Figure 3: Distribution of Spikes and its logarithmic transformation

Table 2 shows the results of estimating Eq. (1). All coefficients are statistically significant at the 5% level. The residuals follow a white noise up to 24 lags based on the chi-square Ljung-Box Q-statistic, LB (24), (significance level of Q is 0.8961).

Table 2: ARMAX model estimating from May 1st 2003 to October 20th 2009

Variable	Coefficient	Std.Dev.	T-statistic	P-value
1. CONSTANT ($\beta 0$)	3.6602	0.09168	39.9243	0.0000
2. AR{1} ($\beta 1$)	1.1321	0.03255	34.7777	0.0000
3. AR{2} ($\beta 2$)	-0.1559	0.02890	-5.3954	0.0000
4. MA{1} ($\theta 1$)	-0.8967	0.01964	-45.6521	0.0000
5. Gasprice ($\phi 1$)	0.0752	0.01187	6.3313	0.0000
6. Importsm ($\phi 2$)	0.0001	0.00003	4.6742	0.0000
7. HDD ($\phi 3$)	0.0083	0.00187	4.4205	0.0000
8. CDD ($\phi 4$)	0.1493	0.01241	12.0282	0.0000

The results confirm that the gas variable effect is statistically significant at the 5% level and that an increase in gas prices of $1US/MMbtu translates into an increase in electricity Spikes prices by a factor of exp (0.0752) = 1.077. Since the Spikes average price is around 98.13$/Mwh (Table 1), an increase in gas prices of $1US/MMbtu induces an increase in the average electricity price by 7.7 $CAN/Mwh (the 75% quantile Spike price is 109.74$/Mwh so the implied gas price increase is 8.6$/MMbtu).

[1] See Box and Jenkins (1976) for a discussion of ARMA modelling approach and Bierens (1987) for ARMAX.

It is worth mentioning that such an increase is compatible with power plants using gas turbines with heat rates in the range, 7,000-10,000 Btu/kWh, which is the heat rate range for such natural gas power plants (see for instance EIA, 2010b). This result suggests that the gas price variability is transferred directly to the electricity prices as opposed to (Rueda and Marathe, 2005) results. Indeed, using Dawn Index as a proxy for gas prices, they find that gas is not important in explaining Spikes prices compared to other variables and they claim that "this could be due to the fact that most of the power plants have long-term gas contracts and therefore have only an indirect effect on the real-time IMO price".

3.3 Granger causality testing

The Granger causality test consists in determining whether the lag of one variable has an impact on the behaviour of another variable (Gelper and Croux, 2007). We perform linear Granger causality within a Vector Autoregressive (VAR) model. The Granger causality involves volatility of the gas price (DIFFGasprice = $\text{Gasprice}_t -$ Gasprice_{t-1}) and volatility of electricity price (DIFFSpikes = $\text{Spikes}_t -$ Spikes_{t-1}) as variables of interest. Since the models VAR (p) are nested within each other, we base our choice in deciding the correct lag order (p) on information criterions (AIC and SBC) and on the likelihood ratio test. The following equation shows the VAR specification:[2]

$$\begin{cases} \text{DIFFSpikes}_t & = \sum_{i=1}^{12} \alpha_{\text{i}} * \text{DIFFSpikes}_{t-\text{i}} + \sum_{i=1}^{12} \beta_{\text{i}} * \text{DIFFGasprice}_{t-\text{i}} + \varepsilon_t \\ \text{DIFFGasprice}_t & = \sum_{i=1}^{12} \delta_{\text{i}} * \text{DIFFSpikes}_{t-\text{i}} + \sum_{i=1}^{12} \gamma_{\text{i}} * \text{DIFFGasprice}_{t-\text{i}} + \varphi_t \end{cases} \tag{2}$$

where $\binom{\varepsilon_t}{\varphi_t}$: White noise vector.

Tables 3 and 4 report the results of estimating Eq. (2). First, the estimated model shows that the lags of the variable DIFFGasprice, has an additional power in forecasting (explaining) DIFFSpikes and not the opposite. In fact, based on Fisher test, the null hypothesis ($H_0 : \beta_1 = \beta_2 \cdots = \beta_{12} = 0$) with respect to DIFFSpikes as the dependant variable is rejected (P-value=0.0001) and the null hypothesis ($H_0 : \delta_1 = \delta_2 \cdots = \delta_{12} = 0$) which involves DIFFGasprice as the dependent variable and the lags of DIFFSpikes as the explanatory variables is not rejected (p-value=0.5699). Second, The residuals of the system follow a white noise up to 24 lags based on the chi-square Ljung-Box Q-statistic, (significance level of $Q = \binom{0.5505}{0.9991}$).

4 Imports Effect

Ontario electricity market is linked with two Canadian markets (Quebec and Manitoba) and three US control areas (New York, Michigan and Minnesota). Between 2006 and 2009, Ontario has been a net exporter. Therefore, one would expect that Ontario is importing electricity only if the imports help reduce electricity prices rather than the opposite. However, Arciniegas and Arciniegas Rueda (2008), using daily average of the variable imports in their time series model, find that the imports coefficient has a significant positive sign, meaning that imports are associated with an increase in the daily electricity spike price. Our econometric model (Table 2) leads to the same result. On the other hand, using higher frequency data (hourly data), we find that the coefficient of imports (with 24h lag) appears with a statistically significant negative coefficient/sign, which supports the idea that such trades help reducing electricity prices, as a consequence of arbitrage opportunities being exploited. Moreover, by using Granger-causality tests, we show that there is a Granger-causality between Ontario electricity prices and imports in both directions. This (Granger) causality is however more important in the direction "electricity price to imports". Since approximately 80% of export trades from Ontario are with New York market, we have conducted a causality test between the variables Spread (New-York Prices – Ontario electricity prices) and imports. The results confirm the earlier conclusion: trade is linked with arbitrage opportunities.

[2] See Geweke (1986) for more information of Granger causality within a VAR model.

Table 3: Estimated VAR (12) with DIFFSPIKES as the dependant variable from May 1st 2003 to October 20th 2009

Variable	Lag	Coefficient	Std. Dv.	T-statistic	P-value
DIFFSpikes	**1**	**-0.7663**	**0.0250**	**-30.7130**	**0.0000**
	2	**-0.6772**	**0.0313**	**-21.6343**	**0.0000**
	3	**-0.5860**	**0.0352**	**-16.6499**	**0.0000**
	4	**-0.5312**	**0.0376**	**-14.1311**	**0.0000**
	5	**-0.4703**	**0.0391**	**-12.0205**	**0.0000**
	6	**-0.3755**	**0.0400**	**-9.3788**	**0.0000**
	7	**-0.3205**	**0.0400**	**-8.0059**	**0.0000**
	8	**-0.2976**	**0.0391**	**-7.6160**	**0.0000**
	9	**-0.2523**	**0.0374**	**-6.7435**	**0.0000**
	10	**-0.2057**	**0.0351**	**-5.8648**	**0.0000**
	11	**-0.1342**	**0.0312**	**-4.3030**	**0.0000**
	12	**-0.0868**	**0.0249**	**-3.4814**	**0.0005**
DIFFGasprice	1	-5.0999	5.2725	-0.9673	0.3336
	2	**16.2325**	**5.2743**	**3.0777**	**0.0021**
	3	-0.3652	5.2914	-0.0690	0.9450
	4	**17.2317**	**5.2872**	**3.2591**	**0.0011**
	5	**22.4845**	**5.3045**	**4.2388**	**0.0000**
	6	4.5897	5.3289	0.8613	0.3892
	7	0.8965	5.3239	0.1684	0.8663
	8	-1.6706	5.3277	-0.3136	0.7539
	9	2.3315	5.3270	0.4377	0.6617
	10	-0.9846	5.3226	-0.1850	0.8533
	11	2.7133	5.3173	0.5103	0.6099
	12	**-11.0669**	**5.3206**	**-2.0800**	**0.0377**

4.1 Description of data and variables

This dataset was also obtained by merging three databases, coming from the IESO (IESO, 2010), Environment Canada (EC, 2010) and NYISO (NYISO, 2010). It includes HOEP, import volumes, pre-dispatch price, Ontario temperature and NY zone A hourly electricity price. The data was collected from June 1st 2005 to October 20th 2009, including weekends and public holydays. In total, our raw data have 38,472 observations. Table 5 reports summary statistics of each variable.

1. HOEP ($CAN/MWh) is the dependant variable.
2. Import volumes (Imports) (MW).
3. NY zone A hourly electricity price (Nymprice) ($US/MWh). NY zone A is associated with the interfaces with Ontario and Approximately 80% of export trades from Ontario are with New York market.
4. Pre-dispatch price (Predispatch) ($CAN/MWh). The market operator provides the markets participants pre-dispatch schedule prices based on the latest information on supply and demand in order to maximize their expected economic gains.
5. Ontario temperature (Tempm) (°C). Variable measured as the average of Toronto, Ottawa, Windsor and Sudbury hourly temperature. However, we are going to use the variables HDH (heating degree-hours) and CDH (cooling degree-hours) with 21°C as the base temperature.

4.2 Preliminaries data analysis

Preliminary data inspection of the dependent variable HOEP reveals a few features requiring adjustments. First, some observations of the variable HOEP have a negative value (0.67% of them). To allow for negative prices in our modelling framework, we re-scale the actual price with respect to a lower bound (54.08= minimum of HOEP+2). Second, it appears that the values of HOEP in February 18th 2008 at the time 11:00 and 12:00 are high enough to be considered as normal values (Ontario temperature isn't the cause;

Table 4: Estimated VAR (12) with DIFFGASPRICE as the dependant variable from May 1st 2003 to October 20th 2009

Variable	Lag	Coefficient	Std. Dv.	T-statistic	P-value
DIFFSpikes	1	-0.0001	0.0001	-1.0483	0.2947
	2	-0.0001	0.0001	-0.3845	0.7007
	3	0.0001	0.0002	0.6156	0.5382
	4	0.0000	0.0002	0.2373	0.8124
	5	0.0001	0.0002	0.6909	0.4897
	6	0.0002	0.0002	0.9882	0.3232
	7	0.0001	0.0002	0.6087	0.5428
	8	0.0001	0.0002	0.2850	0.7757
	9	0.0002	0.0002	1.3297	0.1838
	10	0.0001	0.0002	0.3025	0.7623
	11	0.0000	0.0001	0.3201	0.7489
	12	0.0000	0.0001	0.1015	0.9192
DIFFGasprice	**1**	**-0.0128**	**0.0251**	**-0.5096**	**0.0104**
	2	0.0283	0.0251	1.1275	0.2597
	3	-0.0266	0.0252	-1.0558	0.2912
	4	0.0203	0.0252	0.8054	0.4207
	5	-0.0491	0.0252	-1.9445	0.0520
	6	0.0494	0.0254	1.9473	0.0517
	7	**0.0606**	**0.0253**	**2.3904**	**0.0169**
	8	-0.0186	0.0254	-0.7326	0.4639
	9	-0.0124	0.0254	-0.4889	0.6250
	10	0.0179	0.0253	0.7050	0.4809
	11	0.0097	0.0253	0.3851	0.7002
	12	0.0425	0.0253	1.6770	0.0937

Table 5: Summary statistics of the variables from June 1st 2005 to October 20th 2009 ($n = 38,472$)

Variables	Min	25%-quantile	Median	75%-quantile	Max	Mean	Std.Dev.
HOEP	-52.08	30.92	40.61	59.20	1,891.14	48.19	34.13
Imports	0.00	427.00	830.00	1,291.00	4,562.00	923.01	630.37
Tempm	-25.65	-0.25	9.92	18.33	34.22	8.71	11.42
CDH	0.00	0.00	0.00	0.00	13.22	0.49	1.51
HDH	0.00	2.68	11.08	21.25	46.65	12.78	10.75
Predispatch	-51.00	33.91	47.30	71.00	1,998.00	56.01	36.42
Nymprice	-716.90	31.73	46.54	65.99	1,228.66	51.27	40.10

0°C). We replace these values by using the average of the temperatures on the hours before and after. Third, a logarithmic transformation of the dependent variable HOEP was used because of right asymmetry. Figure 4 shows the sample distribution of HOEP and its logarithmic transformation (log (HOEP)). Further examination of the autocorrelation function indicates the presence of a 24-hour seasonality with respect to HOEP. This seasonality causes non-stationarity (ADF t-test (calculated) = -0.56 > ADF t-test (observed) = -1.95 at the 5% level). Thus, seasonal differencing of 24h order is needed to render HOEP stationary; the ADF t-test (calculated) = -47.91 < ADF t-test (observed) = -1.95 at the 5% level). Accordingly, Eq. (3) shows the dependent variable used for our study. The current dependant variable represents approximately the growth rate of HOEP over 24 hours based on Taylor's polynomial approximation.

$$\text{DIFFHOEPL24} = \log\left(\text{HOEP}_t + 54.08\right) - \log\left(\text{HOEP}_{t-24} + 54.08\right) \cong \frac{\text{HOEP}_t - \text{HOEP}_{t-24}}{\text{HOEP}_{t-24} + 54.08} \tag{3}$$

Similarly, inspection of the autocorrelation function exhibit 24h seasonality regarding all explanatory variables. We apply a seasonal differencing of 24h order for each variable. The resulting variables are displayed by the Eq. (4).

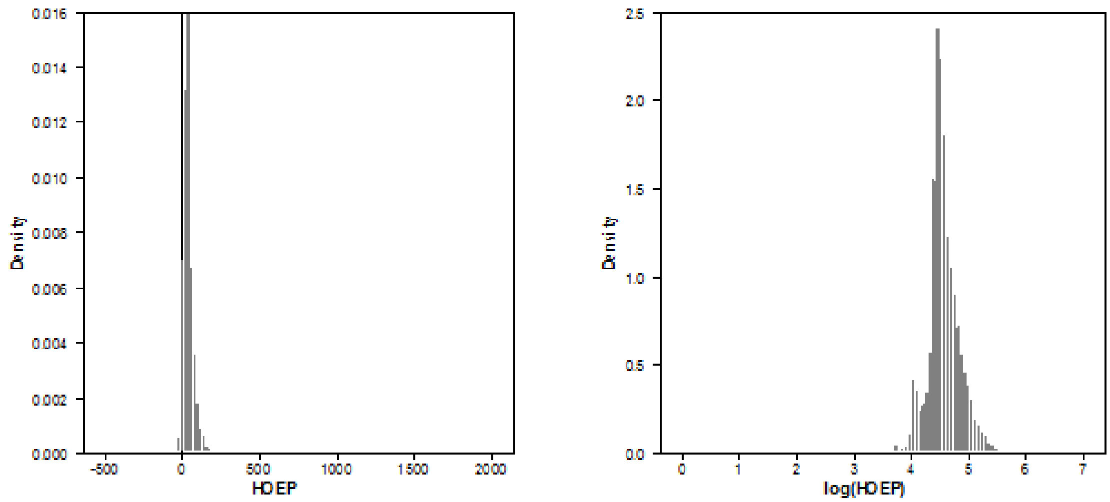

Figure 4: Distribution of HOEP and its logarithmic transformation

$$\mathrm{DIFFV}_t^i = V_t^i - V_{t-24}^i = (1 - L24)V_t^i \tag{4}$$

where V^i is the explanatory variable i and L is the lag operator.

4.3 ARMAX-ARCH model

Stable variance is one of the basic hypotheses required in standard regression models. The most popular approach for analysing time-varying variances is the autoregressive conditional heteroscedasticity (ARCH) framework (Engle, 1982). This model was generalized later by Bollerslev (1986) as the Generalized Autoregressive Conditional Heteroscedasticity (GARCH). In our modelling approach, we combine ARMAX and ARCH models. First, based on the autocorrelation and partial autocorrelation functions of the growth rate of HOEP (DIFFHOEPL24) and given the information criterions AIC and SBC, we identified the autoregressive order 5 and the moving average order 24 as appropriate. We support our finding by checking the adequacy of the model ARMA (5, 24). The model reveals an adjusted R2 of 69%. The empirical autocorrelation function of the residuals follow a white noise up to 24 lags based on the chi-square Ljung-Box Q-statistic, LB(24), (P-value = 0.069). As expected, the distribution of the estimated residuals is leptokurtic with heavy tails. Indeed, the estimated residuals have a right asymmetry (P-value (Skeweness) $= 0 < 0.0001$) with high positive peaks (P-value (Kurtosis excess) $= 0 < 0.0001$). Second, the squared residuals are auto-correlated, the chi-square test statistic for autoregressive conditional heteroscedasticity up to 24 lags is statistically significant at the 5% level (P-value < 0.0001), which leads to a possible ARCH effect. Given the information criterions and the maximal significant lag criterion, we obtain the following ARMAX-ARCH specification.

$$\left\{ \begin{array}{ll} \mathrm{DIFFHOEPL24}_t = \sum_{i=1}^{5} \alpha_i * \mathrm{DIFFHOEPL24}_{t-i} + \sum_{i=1}^{24} \beta_i * \varepsilon_{t-i} + \sum_{i=1}^{5} \gamma_i * \mathrm{DIFFV}_t^i + \varepsilon_t & (5) \\ \varepsilon_t = Z_t \sqrt{H_t} \quad \text{where} \quad H_t = \varphi_0 + \sum_{i=1}^{10} \varphi_i \varepsilon_{t-i}^2 \quad \text{and} \quad Z_t \sim N(0,1) & (6) \end{array} \right.$$

Eq. (5) represents the mean equation for the growth rate of HOEP and Eq. (6) the conditional variance equation.

Table 6 reports the results of estimating Eqs. (5) and (6). All of the coefficients in the mean shown in Eq. (5) are statistically significant at the 5% level, apart from the coefficient of the second order autoregressive term. In terms of the variance equation, the conditional variance is positive ($\varphi_0 = 0.0053$ and $\varphi_i \geq 0$ for $i = 1, \ldots 10$) and the non-conditional variance is stable $\left(\sum_{i=1}^{p} \varphi_i = 0,6797 < 1\right)$.[3]

Table 6: ARMAX-ARCH estimating from June 1st 2003 to October 20th 2009

	Variable	Lag	Coefficient	Std.Dev.	T-statistic	P-value
1	DIFFHOEPL24	**1**	**0.673700**	**0.004524**	**148.917270**	**0.000000**
2		2	-0.000429	0.005452	-0.078630	0.937330
3		**3**	**0.023700**	**0.005109**	**4.645180**	**0.000003**
4		**4**	**0.031300**	**0.004835**	**6.478810**	**0.000000**
5		**5**	**0.048300**	**0.003621**	**13.329710**	**0.000000**
6	Mvg Avge	**1**	**0.026000**	**0.001050**	**24.723190**	**0.000000**
7		**2**	**0.009151**	**0.001073**	**8.527470**	**0.000000**
8		**3**	**0.017700**	**0.001168**	**15.125440**	**0.000000**
9		**4**	**0.012400**	**0.001204**	**10.257100**	**0.000000**
10		**5**	**0.004578**	**0.001153**	**3.969290**	**0.000072**
11		**6**	**0.005480**	**0.001134**	**4.834140**	**0.000001**
12		**7**	**0.004953**	**0.001108**	**4.469260**	**0.000008**
13		**8**	**0.006150**	**0.001177**	**5.223750**	**0.000000**
14		**9**	**0.005968**	**0.001110**	**5.377290**	**0.000000**
15		**10**	**0.007683**	**0.001075**	**7.143870**	**0.000000**
16		**11**	**0.010200**	**0.001033**	**9.858150**	**0.000000**
17		**12**	**0.005436**	**0.001054**	**5.159970**	**0.000000**
18		**13**	**0.007822**	**0.001049**	**7.455180**	**0.000000**
19		**14**	**0.012300**	**0.001023**	**12.025120**	**0.000000**
20		**15**	**0.011200**	**0.001070**	**10.455110**	**0.000000**
21		**16**	**0.007872**	**0.001018**	**7.734410**	**0.000000**
22		**17**	**0.010200**	**0.000995**	**10.260900**	**0.000000**
23		**18**	**0.010800**	**0.001021**	**10.536010**	**0.000000**
24		**19**	**0.014000**	**0.000988**	**14.183490**	**0.000000**
25		**20**	**0.016600**	**0.001013**	**16.426270**	**0.000000**
26		**21**	**0.015000**	**0.001015**	**14.746460**	**0.000000**
27		**22**	**0.011600**	**0.001009**	**11.447090**	**0.000000**
28		**23**	**0.029500**	**0.000883**	**33.432280**	**0.000000**
29		**24**	**-0.933500**	**0.000923**	**-1011.807930**	**0.000000**
30	DIFFIMPORTS		**-0.000011**	**0.000001**	**-10.761610**	**0.000000**
31	DIFFCDH		**0.009527**	**0.000402**	**23.717550**	**0.000000**
32	DIFFHDH		**0.000225**	**0.000076**	**2.972080**	**0.002958**
33	DIFFPREDISPATCH		**0.002014**	**0.000019**	**106.071490**	**0.000000**
34	DIFFNYMPRICE		**0.000026**	**0.000012**	**2.176430**	**0.029523**
35	φ_0		**0.005352**	**0.000031**	**171.003320**	**0.000000**
36	φ	**1**	**0.333200**	**0.004667**	**71.393990**	**0.000000**
37		**2**	**0.181400**	**0.002836**	**63.946990**	**0.000000**
38		**3**	**0.068800**	**0.002455**	**28.003520**	**0.000000**
39		**4**	**0.028300**	**0.001895**	**14.939020**	**0.000000**
40		**5**	**0.005142**	**0.001588**	**3.238760**	**0.001201**
41		**6**	**0.007469**	**0.001480**	**5.047950**	**0.000000**
42		**7**	**0.026300**	**0.001013**	**26.015940**	**0.000000**
43		8	0.001408	0.001006	1.399600	0.161633
44		**9**	**0.006966**	**0.001143**	**6.094810**	**0.000000**
45		**10**	**0.020700**	**0.000731**	**28.309580**	**0.000000**

It is interesting to note that the coefficient of the variable DIFFIMPORTS is negative while the variable imports appears with a positive sign in the daily data model (Section 3) as in the study of Arciniegas and Arciniegas Rueda (2008). The expected effect of imports, however, is that they should participate in reducing Ontario prices rather than the opposite.

One explanation for such seemingly "contradiction" could be that the positive signs in the last two models can be explained by the fact that importers of electricity into Ontario receive their offers' prices even if they are higher than spot prices. Therefore an increase in imports from neighboring markets at moments when prices in such markets are even higher than Ontario prices would lead into increased bid prices and consequently

[3] The conditional and non-conditional variances are defined as $H_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i \varepsilon_{t-i}^2$ and $\dfrac{\varphi_0}{1 - \sum_{i=1}^{p} \varphi_i}$ respectively.

spot prices. Such possible market behavior while not investigated in our analysis would deserve a further thorough analysis to avoid strategic use of imports price guarantees. On the other hand the negative sign in the hourly imports (with 24 lag) confirms the use of imports as an arbitrage tool, as one would expect.

4.4 Granger causality testing

We estimate a VAR (11) model for DIFFHOEP (HOEP$_t-$ HOEP$_{t-24}$) and DIFFIMPORTS (Imports$_t-$ Imports$_{t-24}$). The estimated model shows that the lags of the variable DIFFHOEP have an additional power in forecasting (explaining) DIFFIMPORTS (Table 7). We find similar results in the other causality direction (Table 8). The causality is however stronger in the "prices → imports" direction. This means that a difference in price leads to an increase in imports, more than the other way around.

Table 7: F-test, DIFFIMPORTS as the dependant variable

Variable	F-statistic	P-value
DIFFIMPORTS	3705.8712	0.0000
DIFFHOEP	52.9932	0.0000

Table 8: F-test, DIFFHOEP as the dependant variable

Variable	F-statistic	P-value
DIFFIMPORTS	18.9162	0.0000
DIFFHOEP	1680.8858	0.0000

Since approximately 80% of export trades from Ontario are with New York market, we have conducted a causality test between the variables DIFFIMPORTS and DIFFNYONT (diffNyprice - diffHOEP). A VAR (7) is estimated. We find that DIFFIMPORTS (Granger) causes DIFFNYONT (Table 9) and vice versa (Table 10). However, the causality is stronger in the "DIFFNYONT → DIFFIMPORTS" direction.

Table 9: Test-F, DIFFNYONT as the dependant variable

Variable	F-statistic	P-value
DIFFIMPORTS	4,7459	0,0000
DIFFNYONT	1721,0999	0,0000

Table 10: Test-F, DIFFIMPORTS as the dependant variable

Variable	F-statistic	P-value
DIFFIMPORTS	6109,5939	0,0000
DIFFNYONT	11,2028	0,0000

These results clearly show that price differentials between New York and Ontario Granger-cause electricity imports to Ontario, reflecting a working market. Along with the previous results on the impact of imports on electricity price, we obtain a clear illustration of integrated electricity markets achieving what they are designed to.

5 Conclusion

Electricity reforms open up markets to increased competition. Integration of fuels and markets has been much less studied in the electricity reform literature. This paper contributes to the understanding of the impact of natural gas and trade on local electricity price. Natural gas is of particular importance due to aspirations to move to less carbon intensive electricity generation. In the Ontario market, we find that while natural gas plants are the marginal plants only during periods of extremely high demands, the gas price is an important factor in explaining electricity prices. Moreover, our results suggest that the gas price variability is transferred directly to electricity prices on a short term basis. This effect will very likely continue to grow in the coming years on reaction to the Canadian policy on climate change. Indeed, the coal share in the supply mix will decline in favor of less polluting energy sources such as renewable energy and natural gas.

On the other hand, it is expected that electricity imports to participate in reducing electricity. However, in Ontario, daily spike price data show the opposite effect, while hourly data confirm such expectations. Our paper contributes, in this regards, to establish that imports are beneficial to markets and that interconnections can have significant value. Establishing such value would be a further topic to investigate. Also, since exporters of electricity to Ontario receive their offers' prices even if they are higher than spot prices, further analysis would be needed to check whether such guarantees are not creating incentives for exporters to game the system and avoid "fully exploiting" possible arbitrage opportunities.

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