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Abstract

The carbon tax, imposed on July 1 2012, placed a substantial impost on electricity prices. With the repeal of the tax on July 17 2014, the question as to how much of the tax saving will be passed back to consumers is of consider able interest as it is a test of how competitive the electricity generation and retail sectors are. This statistical investigation addresses the first part of the question, that is, the extent to which the repeal of the tax has been passed back though wholesale electricity prices. This is intended to serve as a benchmark against what consumers might expect to see in retail electricity prices and their utility bills.

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Passing the Repeal of the Carbon Tax Back to Wholesale Electricity Prices

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The carbon tax, imposed on July 1 2012, placed a substantial impost on electricity prices. With the repeal of the tax on July 17 2014, the question as to how much of the tax saving will be passed back to consumers is of considerable interest as it is a test of how competitive the electricity generation and retail sectors are.

This statistical investigation addresses the first part of the question, that is, the extent to which the repeal of the tax has been passed back though wholesale electricity prices. This is intended to serve as a benchmark against what consumers might expect to see in retail electricity prices and their utility bills.

To answer this question it is necessary to create a basis for comparison. The basis used here is pre carbon tax wholesale electricity prices from 1 January 2002 to 30 June 2012. These prices are then compared to wholesale prices while the tax was in place, and after the carbon tax repeal to 26 August 2014. A statistical model for the wholesale electricity market is used to facilitate this comparison

In the first part of this report descriptive price statistics are provided to show some the important characteristics of the data and highlight some of the issues around isolating the effects of the carbon tax and its repeal. In the second part of report the modelling methodology used to address these issues is outlined and the key findings are presented. These findings include the proportion of the tax that is presently being passed back to wholesale electricity prices and the reduction in retail tariffs if the retail sector is competitive. Last, a more technical description of the methodology is provided that focuses on the reliability of the estimates.

The Data

The primary data used are half hourly prices and demand sourced from the Australian Electricity Market Operator (AEMO), converted to real 2014 dollars using the CPI. There are over 180,000 observations prior to the tax and over 35,000 observations while the tax was in place. At the time this analysis was done the number of observations after the repeal was 1,729. However, the effective sample size is smaller as prices are correlated over time. It is possible to correct for the effective sample size to allow a comparison of average prices

between periods, as reported in Table 1. Effective sample sizes are discussed later in this report.
The differences in mean prices between the pre-tax, tax and post tax periods vary considerably between the NEM regions. The same is true for the differences between the tax and post-tax means which are of the greatest interest. However, the standard deviations of these means are sufficiently large relative to their actual values to only allow indicative conclusions at this stage. In particular, at the time of writing it is not possible to come to any reliable conclusions regarding the impact of the tax and its repeal just using these data. It is interesting that the standard errors of the mean are larger in the pre-tax period in the northern regions and larger in the southern regions after the carbon tax was introduced. However, a considerably larger post tax sample would be needed to establish if these differences are statistically significant.

Table 1. Wholesale spot market price means and sample size corrected standard deviations of the mean, prior to, during and after the repeal of the carbon tax.

Region	Mean			Standard Deviation of the Mean		
	Pre-Tax	Tax	Post-Tax	Pre-Tax	Tax	Post-Tax
NSW	47	54	34	11.6	8.1	6.5
QLD	43	63	26	14.3	9.7	4.2
SA	51	66	44	9.5	16.9	17.6
Vic	41	55	34	12.1	15.1	15.2

Comparing the means of wholesale electricity prices is inherently problematic. In rare instances, which can be brought on by weather conditions and system constraints, prices may fall below zero (forcing generators to pay if they wish to stay on line) or increase more than 1,000 fold above a typical daily average. These extreme price events, especially high price events, have a large influence on average price and price variability.

Rank-based measures are not sensitive to extreme values and so can be used to characterise the distribution of electricity prices. These include the percentiles, for example the 50th percentile or median, the point separating the 50 per cent of the highest prices from the 50 per cent of lowest prices. Similarly, the 20th and 80th percentiles bound the central 60 per cent of all prices.

Percentiles of the wholesale electricity prices in the pre-tax, tax and post-tax period are shown in Table 2. Comparing the percentiles with the means set out in Table 1 makes the right skew in the price distribution clear. The means are generally above the 80th percentile as opposed to being near the median. The percentiles are more stable than the means between regions as are the differences between percentiles in pre-tax, tax and post tax periods.

Table 2. Electricity spot market price percentiles prior to, during and after the repeal of the carbon tax.

Period	1st	20th	Median	80th	99th
			New South Wales		
Pre-Tax	14	23	29	43	182
Tax	41	49	52	56	94
Post-Tax	21	27	32	39	64
			Queensland		
Pre-Tax	13	21	26	40	182
Tax	32	48	53	59	93
Post-Tax	13	18	24	32	61
			South Australia		
Pre-Tax	10	20	34	47	181
Tax	27	41	52	67	220
Post-Tax	9	26	35	44	60
			Victoria		
Pre-Tax	10	18	30	44	143
Tax	35	41	49	56	110
Post-Tax	14	25	31	40	77

A comparison can be made of the change in median prices in the pre-tax, tax and post-tax periods. Calculating a standard error or confidence interval for the median needs to take into account the skewness of the price distribution as well as effective sample size. The method used is discussed in the technical section of this paper. The differences in median price between the pre-tax period and the periods during and after the tax are shown in Table 3. The 95 per cent confidence intervals for these differences are also shown.

The imposition of the carbon tax is associated with a $19 to $26 per MWH increase in the median prices across the NEM regions. The repeal of the tax has seen median prices return to near their pre-tax levels. Prices in Queensland have been significantly below their pre tax levels. Clearly the overall drop in median prices is highly significant even over the relatively short time since the tax has been repealed. However, there are a number of other factors that may be influencing prices as well.

Table 3. The difference in the median prices during and after the repeal of the carbon tax from the pre-tax base along with the 90 per cent confidence bounds.

	Carbon Tax			Tax Repealed		
Region	**Lower**	**Estimate**	**Upper**	**Lower**	**Estimate**	**Upper**
NSW	23.3	23.4	23.5	1.3	3.0	3.8
QLD	26.4	26.6	26.8	-4.8	-2.6	-0.76
SA	18.6	19.1	19.5	0.4	0.7	1.0
Vic	19.2	19.4	19.6	-1.2	1.6	4.1

The Pass Back

Attributing price change differences to the carbon tax on the basis of observed prices can be misleading given:

- The short length of the post tax period and the influence of weather conditions over that period;
- Differences in climatic conditions in the pre-tax period and when the tax was in place; and
- Changes to the structure of the market over time, notably the increase in solar and wind generation.

A controlled comparison with less potential for bias due to excluded factors affecting price can be carried out using a statistical model. This uses covariates to take into account other factors that influence wholesale electricity prices and so isolates the impact of the carbon tax. These covariates include current and past trends in demand, weather conditions, and time of day. Structural changes in the market and the carbon tax are represented by indicator variables that allow for structural breaks over different time periods. The model is discussed in the technical note at the end of this document.

The influence of extreme price events on the fit of the model was limited by truncating the price distribution. The lowest one per cent and the highest one per cent of observed prices were removed, leaving the central 98 per cent of the price distribution for analysis.

The model was used to predict prices prior to and during the imposition of the tax and after its repeal. The prediction errors are the residual or remaining uncontrolled variation in price after allowing for the influence of covariates, with the prediction errors prior to the tax forming the baseline used for comparison. Two counterfactual simulations were generated, one in which the carbon tax was not imposed and one in which the tax was imposed but not repealed. The median differences between the baseline and counter factual model prediction errors give an estimate of the price impact of the tax and its repeal. They also allow inferences to be drawn about the significance of the impacts.

The results of the modelling are presented in Table 4. The model produces a much tighter estimate of the impact of the carbon price across the NEM regions, with the median impact on price averaging a little over $27/MW hour. The estimated impact of the repeal is also more consistent across regions. The estimated differences between the median pre and post tax prices are significantly greater than zero in all of the regions indicating that most, but not all, of the tax has been passed back to the wholesale market.

Table 4. The modelled difference in the median prices during and after the repeal carbon tax from the pre-tax base along with the 90 per cent confidence bounds.

Region	Carbon Tax			Tax Repealed		
	Lower	Estimate	Upper	Lower	Estimate	Upper
NSW	26.2	26.6	27.1	2.6	4.2	5.9
QLD	26.6	27.0	27.5	0.1	2.0	4.1
SA	27.5	28.1	28.8	3.1	5.7	8.2
Vic	26.1	26.7	27.3	3.3	5.5	7.8

The pass back to the wholesale market can be calculated as the ratio of the change in prices due to the repeal and the change in prices due to the tax. Again it is possible to place confidence bounds about these estimates. The estimated percentage of the carbon tax passed back to wholesale prices since the repeal of the tax is shown in Table 5 along with the 90 per cent confidence bounds. The pass back ranges from 79 per cent in Victoria to 92 per cent in Queensland and averages about 84 per cent. The 5 per cent lower bound across all regions is over 70 per cent with an average lower bound of about 76 per cent.

Table 5. The estimated percentage of the carbon tax passed back to wholesale prices after the repeal with 90 per cent confidence bounds.

Region	Lower Bound	Estimate	Upper Bound
NSW	78	84	90
QLD	85	92	100
SA	71	80	89
Vic	71	79	88

The Benchmarks

The extent to which wholesale prices changes are passed back to consumers depends in large part on the competitiveness of the retail electricity sector in each region. This study provides some benchmarks as to what might be expected.

Nationally, AEMC (2013) estimates the average retail tariff to by about 28 cents per KWH in 2013. The estimated contribution of the carbon tax of 2.7 cents per KWH would be about 9.5 per cent. This in reasonably close to AEMC estimated impost of 9 per cent for the tax.

With an average pass back of the tax of 84 per cent in wholesale prices, retail prices could be expected drop by around 8.1 per cent. With an average lower bound of 76 per cent price could be expected to fall by at least 7.2 per cent.

An update of this analysis will be provided after the wholesale market has had more time to operate after the repeal of the tax and over a greater range of seasonal conditions.

Technical Notes

A regression model was used to predict half hourly prices in the four NEM regions. The modelling framework is adapted from an electricity demand and price forecasting model that forecasts prices and the probabilities of extreme price events over a 48 hour forecast horizon. Documentation of this framework is available at www.analytecon.com.au.

The explanatory variables used to predict prices include:

- Current and levels of demand in each of the NEM regions;
- Current trends in the level and volatility in demand in each of the NEM regions;
- Daily maximum and minimum temperatures in each capital city;
- Fixed factors for time of day, day of the week and season;
- Fixed factors corresponding to different years that are intended to sweep out impacts due to the increase in the supply of unscheduled or renewable energy.
- Indicator variables defining the duration (imposition, then repeal) of the carbon tax; and
- Interaction terms between the carbon tax indicator variable and the fixed factors and weather conditions.

The price distributions were truncated at the 1st and 99th percentiles. The distributions were still strongly right skewed and so the data were transformed using a cubic root prior to model fitting. There are a large number of potential explanatory variables, particularly with respect to demand. There are also substantive correlations between many of the explanatory variables. This raises a concern that the model could easily be over-fitted leading to unstable parameter estimates with respect to the counterfactual market conditions. To address this problem the model was estimated using a regularised regression technique known as the Lasso (Tibshirani, 1996) which is implemented in the R statistical computing language. Lasso penalises dominant contributions of variables to the fit and thereby limits over fitting.

The overall performance of the model is summarised in Table 6. The R-Square values indicate that the model explains about 89 per cent of the variation in regional prices. The Durbin-Watson statistic indicates that there is a high level of correlation in the model errors in al the regions. The Augmented Dickey Fuller test indicates that the price series in each region are stationary.

Table 6. Regional model summary statistics: R-Square, Durbin-Watson (DW) and Augmented Dickey-Fuller (ADF).

Region	R-Square	DW	ADF
NSW	0.89	0.30**	-26.7**
QLD	0.89	0.44**	-27.6**
SA	0.89	0.43**	-31.9**
Vic	0.90	0.34**	-26.8**

*** Indicates the test statistic is significant at the one per cent level.*

Simulations

The counterfactual simulations were constructed by simply setting the indicator variables for the imposition and repeal of the carbon tax to zero and obtaining the residuals as the difference in the actual and predicted prices. Differences in the median errors between the pre-tax period and the periods over which the tax was in place and then repealed are then calculated from the residuals. In turn the differences in medians are used to calculate the pass back.

The exclusion of past prices and not choosing to correct them simplifies the design of the counterfactual simulations and avoids bias that commonly arises in the dynamic specification of the model (Mizon, 1995). However, the effect of serial correlation does need to taken into account when drawing inferences from the results of the simulations. This is done non-parametrically through resampling which also allows the estimation of the standard error and confidence bounds of median prices of a skewed distribution and a ratio statistic like the pass back.

Resampling

The first step of the resampling scheme is to calculate the effective sample size based on the sum of the observed correlation in prices through time. This is done according to Straatsma et al (1986) with the formula

$$N_e = \frac{N}{\tau}$$

where

$$\tau = 1 + 2\sum_{k=1}^{n/2-1} \rho_k$$

and

$$\rho_k = \frac{\mathrm{Cov}\left(P_t, P_{t-k}\right)}{\mathrm{Var}\left(P_t\right)}$$

Where N_e is the effective sample size, N is the sample size, P is price and ρ are the autocorrelations. It is clear from the formula that if prices are perfectly uncorrelated (ρ =0) the actual and effective sample sizes are the same. In contrast, if prices are perfectly correlated (ρ =1) the effective sample size is one.

The second step is to randomly resample the imputed price impacts, with the size of the resample equal to the effective sample size of the original data. Using samples of the appropriate size the medians and the pass back can be computed. Repeating the process a large number of times (10,000 replicates) generates an empirical sample of the medians and the pass back from which the standard errors and confidence intervals were obtained. The results are summarised in Table 7. The same procedure was used to compute the confidence bound about the price medians.

It is clear from the table that the high level of temporal correlation in the model errors greatly reduces the effect sample size relative to the nominal size. The reduction is of the order of 100 fold for when the tax was in place and 40 fold after the repeal. However, the effective sample size is large enough to produce relatively a precise estimate of the median impact on price given the control provided by the model.

Table 7. The sample size (N_e), effective sample size (N), median price impact and the standard error of the median for the period of the carbon tax and its repeal.

Region	Carbon Tax				Tax Repealed			
	N_e	N	Median	SE	N_e	N	Median	SE
NSW	35,374	380	26.9	0.27	1,729	44	4.2	1.01
QLD	34,982	489	27.0	0.25	1,723	33	2.0	1.25
SA	34,877	518	28.4	0.39	1,709	31	5.7	1.57
Vic	35,212	340	26.9	0.34	1,720	26	5.5	1.35

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