Asset beta for gas pipeline businesses

A report for Powerco

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1. Introduction

The Commerce Commission (the Commission) is engaged in a review of the Input Methodologies (the IMs) that it applies in the economic regulation of Transpower, electricity distribution businesses (EDBs) and gas pipeline businesses (GPBs). The review encompasses issues relating to estimation of the weighted average cost of capital (WACC).

Under the current IMs, the Commission estimates a regulated WACC for GPBs on the basis that the asset beta for these businesses is 0.10 higher than for EDBs and Transpower. The Commission's use of an asset beta differential of 0.10 is long-standing, with the rationale for this differential being provided in reports prepared by the Commission's advisor on cost of capital issues, Dr Martin Lally.[1]

Prior to the release of its pending draft report on its review of the IMs, the Commission has released a new report prepared by Dr Lally and invited comments. In this most recent paper, Dr Lally states that he no longer favours a differential between the asset betas for New Zealand EDBs and GPBs because, in his view:[2]

- the reasons that supported his earlier recommendation of an asset beta differential no longer hold true; and
- the submissions to the Commission citing evidence for an asset beta differential are inconclusive.

Dr Lally also introduces an algebraic framework for using evidence about asset beta to inform the magnitude of the appropriate asset beta differential for gas and electricity network businesses. He uses this framework to show that information about differing relative usage of gas and electricity by residential and commercial/industrial customers is unlikely to support a large beta differential.

Powerco has asked us to review and comment on the issues raised by Dr Lally, and our report is structured as follows:

- section 2 reviews and responds to the reasons cited by Dr Lally for amending his earlier opinion in support of an asset beta differential; and
- section 3 examines Dr Lally's framework for assessing the beta differential and shows that, when his assumptions are replaced by inputs informed by data and analysis, it provides support for an ongoing, increased asset beta differential for gas distribution businesses (GDBs), principally because of their exposure to income-related variability in residential demand for gas.

This report is an update to a previous version of the same report, dated March 2016. Since issuing the previous version of the report, we have identified errors in underlying data, sourced from information disclosures, that we used in the analysis presented in that report. This report provides updated analysis and results that are free from these errors. The changes to our analysis give rise to modest increases in our estimates for the asset beta differential and this report therefore supersedes the previous version, which should be set aside. However, the substance of our analysis and conclusions in the previous report are not affected by the errors that we have identified.

[1] Lally, Martin, *The weighted average cost of capital for gas pipeline businesses*, 14 May 2004; and Lally, M, *The weighted average cost of capital for gas pipeline businesses*, 28 October 2008

[2] Lally, Martin, *Review of WACC issues*, 25 February 2016, pp 3, 6-9

2. Previous rationale for a higher beta for GPBs

In his most recent report, Dr Lally states that he no longer favours a higher asset beta for GPBs than for EDBs and Transpower. Dr Lally notes that the reasons that supported his earlier recommendation of an asset beta differential no longer hold true because:[3]

> … the principle [sic] argument for the higher asset beta for the gas businesses that was presented in Lally (2008, section 5.2) is no longer applicable…

In this particular passage of his most recent report, Dr Lally is referring to the proposition that gas pipelines have greater options for growth than electricity lines businesses. Dr Lally has previously taken the view that this factor may give rise to a higher asset beta for GPBs, but he no longer believes this to be the case because:[4]

> …Lally's (2008) analysis was conducted at the time these gas businesses were only subject to the threat of formal regulation rather than formal regulation per se. By contrast, they are now subject to formal regulation, and this affects the argument for the differential in the asset beta.

In our view, there is no evidential support for Dr Lally to step back from the conclusions of his previous advice in relation to the appropriate asset beta differential for GPBs. The significance of Dr Lally's change of view arises because his earlier conclusions formed the basis upon which the IMs currently specify a higher asset beta for GPBs. However, Dr Lally does not present any evidence by way of support for this opinion that the Commission should now alter the IMs in this respect.

Dr Lally's 2004 report had regard to three factors that distinguished the systematic risk of GPBs and electricity lines businesses in recommending a higher asset beta for GPBs. At the time, Dr Lally gave predominant weight to the third of these factors, being the relative use of the two forms of energy by residential and other customer types. Dr Lally's analysis showed that commercial and industrial customers account for 82 per cent of gas usage, whereas the corresponding proportion was just 68 per cent for electricity usage.[5]

In his 2008 report, Dr Lally continued to have regard to the same three factors, and his analysis of the relative use of the two forms of energy by residential and other customer types did not change.[6] However, he also had regard to an additional factor, being the existence of growth options for gas networks that did not exist (or were less extensive) for electricity networks.[7] Dr Lally's 2008 report states that this factor, and the relative use of energy by different customer types, were together particularly relevant in supporting his view in favour of a higher asset beta for GPBs.[8]

In both his 2004 and 2008 reports, Dr Lally recommended an asset beta for GPBs that was 0.10 higher than for electricity lines businesses. The fact that his recommendation did not change as between these two reports implies that the growth options proposition introduced in Dr Lally's 2008 report was not determinative for his conclusion. This implication, in combination with the weight given to both considerations in his 2008 report, sits uneasily with Dr Lally's claim now that the growth options rationale was the most important consideration in favour of a higher asset beta for GPBs.

[3] Lally, Martin, *Review of WACC issues*, 25 February 2016, pp 8

[4] Lally, Martin, *Review of WACC issues*, 25 February 2016, p 6

[5] Lally, Martin, *The weighted average cost of capital for gas pipeline businesses*, 14 May 2004, pp 33-34

[6] Lally, Martin, *The weighted average cost of capital for gas pipeline businesses*, 28 October 2008, pp 63-64

[7] Lally, Martin, *The weighted average cost of capital for gas pipeline businesses*, 28 October 2008, p 62

[8] Lally, Martin, *The weighted average cost of capital for gas pipeline businesses*, 28 October 2008, p 64

In any case, Dr Lally's rationale for why the existence of relatively more growth options for GPBs no longer points to a higher asset beta does not support any change from his earlier views. The context of Dr Lally's 2008 report was that the Commission had decided to declare regulatory control over GPBs and sought to estimate a WACC to apply in that process.[9] In other words, at the time of the 2008 report, the GPBs were already subject to formal regulation and so the same limitations to their growth options that Dr Lally now contends to be the most significant consideration. In our opinion, this does not provide any basis to assume that this factor weighs differently now in any assessment of the asset beta for GPBs.

Dr Lally's 2008 report also relied upon evidence in relation to the use of energy by residential and other customer types to support his conclusion in favour of a higher asset beta for GPBs. The evidence provided by updating this analysis is essentially unchanged – a point that is clear from analysis provided both in our previous report[10] and now by Dr Lally.[11]

The evidence previously relied upon by Dr Lally in favour of a higher asset beta for GPBs over EDBs and Transpower, and which was subsequently relied upon by the Commission, has not materially changed. In our view, Dr Lally has not provided any further evidence that is capable of supporting a change in his position, or supporting the Commission changing its position during its the review of the IMs.

[9] Lally, Martin, *The weighted average cost of capital for gas pipeline businesses*, 28 October 2008, p 8

[10] HoustonKemp, *Comment on the Commerce Commission's cost of capital update paper*, 5 February 2016, pp 10-11

[11] Lally, Martin, *Review of WACC issues*, 25 February 2016, p 7

3. Evidence for a higher asset beta for GDBs

In this section we review the analytical framework proposed by Dr Lally for assessing evidence for an asset beta differential. We propose a number of changes to the structure and assumptions of Dr Lally's framework so as to incorporate a much wider range of information than contemplated by Dr Lally, including the results of econometric analysis of income elasticity of demand that we have performed for New Zealand.

Overall, the application of this framework to incorporate the income elasticity analysis we have undertaken suggests an asset beta differential for GDBs in particular remains appropriate, on account of the significantly higher asset beta that is likely to apply for the residential supply of gas, as compared with the residential supply of electricity.

3.1 Lally's analytical framework

Dr Lally no longer considers that the statistics on relative gas and electricity consumption inform a significant difference in asset betas. In order to demonstrate this, Dr Lally introduces an algebraic framework to inform the magnitude of any gas beta differential. In forming this framework, Dr Lally assumes that:[12]

- residential asset betas are the same for gas and electricity;
- commercial/industrial asset betas are the same for gas and electricity;
- commercial/industrial asset betas are related to residential asset betas through an unknown factor K; and
- the weighted average beta for electricity is 0.34.

Under these assumptions, and on the basis of his own analysis as to the breakdown of consumption of gas and electricity by residential and commercial/industrial users, Dr Lally chooses a value for K and solves for residential and commercial/industrial betas, using the following formulae:

$$(0.32)\beta_{resid} + (0.68K)\beta_{resid} = 0.34$$

$$(0.17)\beta_{resid} + (0.83K)\beta_{resid} = \beta_{gas}$$

Values of K greater than one give rise to a positive asset beta differential for gas because the proportion of gas consumed by commercial/industrial customers is greater than for electricity. Under the assumptions made by Dr Lally, regardless of the magnitude of K assumed, the average asset beta for gas cannot exceed the average asset beta for electricity by more than 0.08, as we show at Table 1 below.

Table 1: Lally's analysis of asset beta differential

K	Residential beta	Commercial/ Industrial beta	Electricity beta	Gas beta	Asset beta differential
1	0.34	0.34	0.34	0.34	0.00
2	0.20	0.40	0.34	0.37	0.03
3	0.14	0.43	0.34	0.38	0.04
5	0.09	0.46	0.34	0.39	0.05
∞*	0.00	0.50	0.34	0.42	0.08

** results described are as K approaches ∞*

[12] Lally, Martin, *Review of WACC issues*, 25 February 2016, pp 6-7

In our view, there are some important limitations in the application by Dr Lally of the framework that he proposes to inform the beta differential. In particular, Dr Lally:

- assumes that the same residential and commercial/industrial asset betas apply for electricity as for gas; and
- derives the average asset betas for electricity and gas through weights that derive from their respective volumes.

These assumptions are neither necessary nor justifiable, because:

- we have previously presented evidence, which we develop at section 3.2 below, that the asset beta for residential supply of gas is considerably higher than for the residential supply of electricity; and
- weighting asset betas on the basis of volumes consumed does not adequately reflect the importance of the residential sector to GDBs (or EDBs for that matter).

3.2 Evidence on income elasticity of demand

Dr Lally and ourselves agree that the income elasticity of demand for a product or for a particular class of customers for that product is of particular relevance as an indicator of asset beta.

In our previous report, we identified a number of principles as to why one might expect the income elasticity of gas demand to be greater than for electricity demand, particularly for small customers:[13]

> There are good reasons to expect that New Zealand gas network businesses may face greater risks than New Zealand electricity network businesses. The most important of these is the discretionary nature of gas consumption for many uses. Many common appliances and industrial processes only use electricity. The primary uses of gas, for heating and cooking, compete with electricity and other fuels for all but a few industrial uses. This suggests that supply of gas to small customers, in particular, may be exposed to the risk of being displaced by electricity and other fuels.

A more complete description of these risks is set out in Concept Consulting's report for Powerco.[14]

Our previous report also identified[15] evidence from an Australian working paper that estimated income elasticity of residential demand for gas as being more than three times as high as for electricity.[16] Although the paper is now relatively old and was not published in a peer-reviewed journal, it provides evidence that conflicts with one of the assumptions made by Dr Lally when applying his framework for estimating the asset beta differential.

Dr Lally's report does not refer to the Australian empirical estimates of income elasticity of demand that we identified, although he does highlight the importance of income elasticity of demand as a factor driving asset beta:[17]

> …Colonial appear to be confusing the price elasticity of demand with that of the income elasticity of demand. Only the latter is relevant to beta: differences in beta are driven by differences in sensitivity to GDP shocks, and GDP shocks affect the demand for a product in accordance with its income elasticity of demand, not its price elasticity.

[13] HoustonKemp, *Comment on the Commerce Commission's cost of capital update paper*, 5 February 2016, p 9

[14] Concept Consulting, *Relative long-term demand risk between electricity and gas networks*, 23 January 2016

[15] HoustonKemp, *Comment on the Commerce Commission's cost of capital update paper*, 5 February 2016, pp 9-10

[16] Akmal, A., and Stern. D., *Residential energy demand in Australia – An application of dynamic OLS*, October 2001

[17] Lally, Martin, *Review of WACC issues*, 25 February 2016, p 8

This perspective is also consistent with views expressed in Dr Lally's previous analysis of asset beta for GPBs. For example, in his 2004 report referred to in section 2 above, Dr Lally stressed the importance of income elasticity of demand:[18]

> Firms producing products with low income elasticity of demand (necessities) should have lower sensitivity to real GNP shocks than firms producing products with high income elasticity of demand (luxuries), because demand for their product will be less sensitive to real GNP shocks. Rosenberg and Guy (1976, Table 2) document statistically significant differences in industry betas after allowing for various firm specific characteristics, and these differences accord with intuition about the income elasticities of demand. For example energy suppliers have particularly low betas whilst recreational travel is particularly high.

These words are also repeated verbatim in Dr Lally's subsequent 2008 report.[19]

In this section we describe new empirical analysis of available evidence of the New Zealand income elasticity of demand for electricity and gas services. Our analysis produces results that are broadly consistent with the study by Akmal and Stern to which we have earlier drawn attention. In particular, we find that the residential demand for gas has much greater income elasticities than the residential demand for electricity.

It is important to acknowledge the limitations of our analysis. We have conducted our analysis using quarterly New Zealand data for consumption and prices of electricity and natural gas services, as well as annual and quarterly data on GDP per capita, which we use as a proxy for income. However, we explain further below that there are difficulties with performing analysis with these data, including:

- the relative lack of availability of some consumption data on a quarterly basis; and
- the length of the time series for annual data, which are only available consistently since 1991.

Despite the relatively limited availability of data, we have applied robust time-series econometrics techniques where it is possible to do so and reported the results of these methods. We interpret these results as providing support, alongside the Akmal and Stern analysis, for a conclusion that the income elasticity of residential demand for gas is substantially higher than for electricity in New Zealand.

3.2.1 Consumption, price and income data

We compile data that has been collected by the New Zealand Ministry of Business, Innovation and Employment (MBIE), Statistics New Zealand (Stats NZ), and the International Energy Agency (IEA) that, together, comprise:

- data sets of industrial, commercial and residential consumption of natural gas, at quarterly and annual periodicity;
- data sets of industrial, commercial and residential consumption of electricity, at annual periodicity;
- a data set of expenditure measure GDP per capita, at quarterly and annual periodicity, that we have used as a proxy measure for income;
- data sets of industrial and household natural gas prices, as well as industrial, commercial and residential natural gas prices, at quarterly and annual periodicity;
- indices of wholesale and retail natural gas prices, at quarterly and yearly periodicity, as well as commercial and household natural gas prices, at quarterly periodicity;
- data sets of industrial and household electricity prices, as well as industrial and commercial electricity prices, at annual periodicity;

[18] Lally, Martin, *The weighted average cost of capital for gas pipeline businesses*, 14 May 2004, p 24

[19] Lally, Martin, *The weighted average cost of capital for gas pipeline businesses*, 28 October 2008, p 49

- indices of wholesale and retail electricity prices, at quarterly and yearly periodicity, as well as commercial and household electricity prices, at quarterly periodicity; and
- the consumer price index (CPI), at quarterly periodicity, which we have used to convert GDP and prices to constant dollars terms.

These data sets have been collected by several data providers at different periodicities, and so they are not all of uniform length. Although our longest quarterly and annual data sets have 148 and 54 observations respectively, the requirement for any model to have coincidental data for all variables means that we have been limited to estimating quarterly and annual models with roughly 100 and 20 observations, respectively.

The availability of quarterly consumption data, in particular, is limited. There is no long time series of quarterly data on electricity consumption, and so we are restricted to estimating electricity demand models with annual data. Further, the quarterly natural gas consumption data provided by MBIE, which is our only quarterly data on natural gas consumption, is not truly quarterly prior to 2006. Although the data set contains observations back to the March quarter 1990, there is no within-year variation of those observations until the March quarter 2006, at which point the data begin showing a strong seasonal fluctuation. We have taken steps to inspect and control for this feature of the data, which we discuss further below.

Economic theory and the existing academic literature suggests that consumption, income and price data are very often non-stationary, ie, they either trend, or drift away from a stationary mean, rather than oscillating randomly about it. When analysing economic relationships, it is important to employ methods that control for this feature of the data, since otherwise it is possible to detect a mistaken relationship between variables, when in fact none exists.

The first step of our analysis was therefore to test whether each data set is non-stationary. We employed three approaches to this test, in the order of increasing formality. First, we visually inspect the data.[20] Non-stationarity can often be seen from a simple plot of the data against time, and this step informs whether our formal tests should be seeking a persistent trend, as we would expect in income data, or a 'random walk' that drifts away from a stationary mean over a prolonged period of time.

Second, we conduct a Dickey-Fuller test for non-stationarity, as set out in *Econometric Analysis* by William Greene.[21] Since we are concerned that the errors of the model used to conduct this test are not white noise,[22] as is assumed by the standard Dickey-Fuller test, we use the augmented version of the test. This version uses lagged differences of the observations as an explanatory variable. The number of lags used to test each data set is determined by testing down to the first significant coefficient on the last lag, beginning with the maximum number of lags, as suggested by Schwert (1989).[23]

Finally, we conduct the augmented Dickey Fuller test using the ADF-GLS procedure proposed by Elliot, Rothenberg and Stock (1996).[24] The advantage of this procedure over the classical augmented Dickey-Fuller test is that it has substantially improved power when an unknown mean or trend is present. We therefore use it as a cross check on the augmented Dickey-Fuller test conducted at step two.

[20] All of our econometric analysis was conducted in the statistical software Stata (version 14.1) using standard packages and, in the case of the Engle and Granger test for co-integration (see below), the community contributed package *egranger*.

[21] Greene, William, *Econometric Analysis (7th edition)*, 2012, pp. 948-957.

[22] The errors of a model are the variations in the data not explained or predicted by the model. If our model hypothesises a relationship between data sets y and x of $y = a + b\,x$, then for each time period the error, e, would be $e = y – (a + b\,x)$.

[23] After conducting a large number of simulations, G William Schwert suggested that the largest lag length considered be that given by p = integer part of $[12 \times (T/100)^{.25}]$, where T is the number of observations in the data set. See Greene, William, *Econometric Analysis (7th edition)*, 2012, p. 255.

[24] See Greene, William, *Econometric Analysis (7th edition)*, 2012, p. 256.

Our analysis shows that all of our data exhibit the characteristics of non-stationary data.[25] The results of our tests are shown in Appendix A1 below. These findings suggest a particular approach to the elasticity estimation process, as explained below.

We note above that traditional econometric methods may find spurious relationships when the data sets being inspected are non-stationary. However, the academic literature suggests a number of methods for estimating long run relationships in trending data. Further, if the data sets are found to be co-integrated – ie, the underlying cause of the trend or drift in the data is common across all data sets – then it suggests a method that performs well with small data sets.[26]

This approach necessitates a test for co-integration. If the trend causing non-stationarity is common to our consumption, income and price data sets, then the variation left unexplained by a linear combination of the data sets should be stationary. This is the basis for the Engle and Granger test, which is analogous to applying the Dickey-Fuller test for non-stationarity to the errors of our models.[27] A finding that the errors exhibit stationarity supports the conclusion that the data sets used to estimate the model are co-integrated.[28] We show the results of our tests in Appendix A1 below.

3.2.2 Econometric methods

We begin by estimating ordinary least squares (OLS) models of consumption on income, electricity and natural gas prices, for both electricity and natural gas consumption in the residential and commercial sectors, using our annual data. We log transformed each variable, and the coefficients we estimate therefore represent elasticities in percentage terms. Although these coefficients are susceptible to the allegations of spurious relationships that we describe above, they provide a useful reference point for subsequent analysis.

We then estimate dynamic OLS models of the same relationship.[29] Dynamic OLS provides an efficient estimator in the presence of non-stationarity, and has been shown to be effective at analysing long-run relationships when working with small data sets. It achieves this result by including leads and lags of first differences of the explanatory variables as a robust control for co-integration.

However, including additional differenced variables in our models uses a significant number of the available degrees of freedom when estimated using our limited annual data. Although we test down to the optimal number of leads and lags using a Wald test procedure,[30] much as we did for our augmented Dickey-Fuller tests, we cannot be certain that the optimal number of leads and lags is not greater than the number to which our limited data sets restrict us. For this reason, we are cautious in placing full reliance on the results of these models.

We therefore estimate dynamic OLS models using our larger sets of quarterly data, where the available consumption data enables us to do so. This restricts us to analysing the relationship specified above for residential and commercial gas consumption only. Since these data are quarterly, we also include quarterly

[25] More precisely, we are unable to reject the null hypothesis of non-stationarity for all of our quarterly data sets. While failure to reject non-stationarity is not confirmation of it, we proceed as if our finding had been affirmative.

[26] Another potential approach would be to transform the data to stationarity prior to estimating more rudimentary models. In initial, unreported analysis, we found that models estimated using this approach were poorly fitted and had low explanatory power. We therefore chose to focus on the alternative method discussed.

[27] Greene, William, *Econometric Analysis (7th edition)*, 2012, pp 665-666.

[28] Greene, William, *Econometric Analysis (7th edition)*, 2012, pp. 959-967.

[29] The dynamic OLS method, as developed by Saikkonen (1991), Phillips and Loretan (1991) and Stock and Watson (1993), provides an efficient estimator for long-run relationships when using data sets with differing orders of non-stationarity, and has been used in Australia to analyse the elasticity of energy demand and to produce forecasts of future demand. See Akmal, M, and Stern, D, *Residential energy demand in Australia – An application of dynamic OLS*, October 2001; and AEMO, *Forecasting methodology information paper*, 2013.

[30] Specifically, the procedure tests the restriction that all the coefficients on the last leads and lags are jointly zero at the 0.05 level from the maximum number suggested by Schwert (1989) (see footnote 21) to the first significant lead/lag. See Akmal, M, and Stern, D, *Residential energy demand in Australia – An application of dynamic OLS*, October 2001, p 9; and Greene, William, *Econometric Analysis (7th edition)*, 2012, pp 115-117.

dummy variables in these models to control for seasonality. However, as we noted above, the data is only of a true quarterly nature after the March quarter 2006, and so we restrict the dummies to be equal to zero prior to this period.[31]

The advantage of estimating these models using our quarterly data is that we have sufficient observations to determine the optimal number of leads and lags when applying the dynamic OLS method. The results from these models are therefore robust to issues of non-stationarity and co-integration, and provide a useful point of comparison to our results from models estimated with annual data. The results of our analysis, and more detailed specification of the models employed, can be found in appendix A1 below.

3.2.3 Estimated income elasticities

We set out the income elasticities of demand for electricity and natural gas estimated by our OLS and dynamic OLS models in Table 2 below. We provide full details of the results behind this summary at appendix A1 below.

Table 2: Income elasticities of demand for natural gas and electricity in New Zealand

Model (with data sets used in estimation)	OLS	Dynamic OLS
Annual data		
Income elasticity of residential gas demand (Consumption and P_G from MBIE, P_E from IEA)	3.61 (0.000)	3.84 (0.000)
Income elasticity of commercial gas demand (Consumption, P_G and P_E from IEA)	1.38 (0.000)	1.25 (0.003)
Income elasticity of residential electricity demand (Consumption and P_G from MBIE, P_E from IEA)	0.80 (0.000)	0.82 (0.000)
Income elasticity of commercial electricity demand (Consumption, P_G and P_E from MBIE)	1.37 (0.000)	1.42 (0.000)
Quarterly data		
Income elasticity of residential gas demand (Consumption and P_G from MBIE, P_E from IEA)		4.18 (0.000)
Income elasticity of commercial gas demand (Consumption and P_G from MBIE, P_E from Stats NZ)		1.62 (0.000)

Source: HoustonKemp analysis of data from MBIE, Stats NZ and the IEA
Notes: (1) P-values are reported in parentheses; (2) P-values are calculated with Newey-West standard errors

The results of analysis using both OLS and dynamic OLS indicate that the income elasticity of residential demand for gas in New Zealand is substantially higher than the income elasticity of residential demand for electricity. The results from the OLS models reported in the first column of Table 2 show a ratio of these estimates as 4.51 – broadly consistent with the results reported by Akmal and Stern, which suggest a ratio of 3.62.[32]

We report the results of using dynamic OLS to estimate the same models in the right hand column of Table 2. The results of the models estimated using annual data are similar to those from the OLS models, and support a ratio of 4.68. These results also provide a degree of confidence that the relationship estimated is not spurious. However, as we noted above, the limited number of observations in our annual data may restrict the application of the dynamic OLS method. We therefore cannot fully rely on the results as an indication of the robustness of this relationship.

[31] That is, dummy q_i equals one for quarter *i* from the beginning of 2006, and zero otherwise. This restriction prevents the control for seasonality provided by the dummy from being biased downward by the absence of seasonality in the data prior to 2006.

[32] Akmal, M, and Stern, D, *Residential energy demand in Australia – An application of dynamic OLS*, October 2001, p 22.

Finally, we report the results of estimating the dynamic OLS models for natural gas consumption using our quarterly data. The quarterly data contain a much greater number of observations than the annual data. This allows the dynamic OLS method to be much more effectively employed, providing for a more robust estimate of long-run demand relationships. The income elasticity of residential demand for gas estimated is 4.18, and is therefore not dissimilar to the results from our other models. The uniformity of estimates across multiple approaches provides a degree of confidence in the results of our analysis.

Similarly, in Table 2 we report OLS and dynamic OLS estimates of income elasticity of commercial demand for gas and electricity. These results indicate that commercial gas consumption is much less responsive to changes in income than residential gas consumption, although the reverse is indicated for electricity. Finally, our results indicate that commercial customers have similar levels of income elasticity across fuels.

In section 3.4 we describe how these results can be used to inform asset beta.

3.3 Volume weights for asset beta

Dr Lally's analytical framework uses volumes as the basis upon which to de-compose average asset betas across different residential and commercial/industrial customer groups. However, the use of volume weights is unlikely to be appropriate as a basis for averaging asset beta.

In principle, the correct basis for averaging different values of asset beta across different services is the relative market value of providing those services. In the absence of such information, a better proxy for the value of residential customers to GPBs and EDBs is not the proportion of volumes that are sold to these customers, but rather the share of revenues that is recovered from them.

We have collated data provided by GPBs and EDBs under information disclosures to the Commission that identifies volumes and revenues earned from different tariffs. These data, provided in response to section 8 of the information disclosure template, are not reported by the Commission in its own summary of the disclosures. However, we have derived them from the most recent disclosures that are fully available in spreadsheet format, being:

- the 2014 information disclosures for GPBs;[33] and
- the August 2013 information disclosures for EDBs.[34]

These data do not always clearly distinguish volumes and revenues from residential customers and those for small commercial customers, since they are often supplied under the same tariff. We have attempted to break the data down by identifying volumes and revenues for 'small' customers with demand akin to residential levels and 'large' customers with demand more consistent with medium to large commercial enterprises and industrials. The basis for making this breakdown is necessarily subjective and we considered the following factors:

- the description provided by the service provider in its information disclosure – for example, where a tariff is tagged as being for 'residential' or 'residential and small commercial', we assume that volumes and revenues under this tariff are for 'small' customers;
- the number of customers in each tariff class compared to other tariffs offered by the same provider – we would expect tariffs targeted at small customers to have more customers than those intended for large customers; and
- the average level of consumption per customer in each tariff class – by observing consumption for service providers that do separately identify small customers, we can see that these customers tend to consume on average less than 100 GJ per year (for gas) or 10,000 kWh per year (for electricity).

[33] Available online at http://www.comcom.govt.nz/dmsdocument/14116 and http://www.comcom.govt.nz/dmsdocument/14117.

[34] Available online at http://www.comcom.govt.nz/dmsdocument/11318. We were unable to use Electra's information disclosure because it did not appear to identify separate tariff classes in response to section 8, but rather, separate tariff components.

These data suggest that there is a very significant difference between volume share and revenue share for small customers. For example, on average across GDBs, the volume share of small customers was 21 per cent but the revenue share from exactly the same customers was 62 per cent.

Table 3 below shows the breakdown of this estimate by GDB. By comparison, for EDBs the volume share of small customers was 48 per cent but the revenue share of these customers was 63 per cent.

Table 3: Comparison of volume weights and revenue weights

	Percent volumes from small customers	Percent revenues from small customers
GasNet	21%	74%
Powerco	33%	71%
Vector	16%	56%
Average gas distribution	**21%**	**62%**
Average electricity distribution	**48%**	**63%**

Source: Information disclosures, HoustonKemp analysis

The data in Table 3 suggest that the evidence for significant differences in income elasticity of residential demand between gas and electricity should receive much greater weight in informing an overall beta for gas distribution services than implied by Dr Lally's algebraic framework for analysis. We show the effect of considering this additional information in section 3.4 below.

In section 3.4 below we associate small customer consumption and revenue with data about residential customers that we have estimated in section 3.2 above, and similarly associate large customer consumption and revenue with data on commercial and industrial customers. There is some risk that these associations are not perfect because the information disclosures do not precisely distinguish volumes and revenues earned from residential customers from those earned from other customers.

3.4 Implications for asset beta

In sections 3.2 and 3.3 we provide information that can be used to populate Dr Lally's analytical framework. In particular:

- the results in section 3.2 suggest that, rather than assuming that asset betas for residential gas and electricity supply are the same, it would be more realistic to assume a higher asset beta for residential gas supply; and
- the data collated in section 3.3 provide a basis for weighting such higher asset betas so as to derive a business-level estimate, using revenues earned from different customer classes.

Some transformation to the estimated income elasticities is necessary to provide more useful evidence for asset betas. Income elasticities measure changes in volumes relative to changes in income. However, the ratio of income elasticities between services is unlikely to be directly reflected in the ratio of underlying asset betas because, amongst other considerations, changes in volumes do not flow through to changes in revenue in the same way across gas and electricity services.

Collation of the section 8 information disclosure data indicates that, for small customers, the percentage of revenues through variable charges is higher for electricity distribution than for gas distribution. This indicates that changes in volumes flow in greater proportion to changes in revenue for electricity distribution than for gas distribution.

Table 4: Comparison of proportion of revenue through variable charges

	Percent of small customer revenue	Percent of large customer revenue
GasNet	47%	63%
Powerco	59%	71%
Vector	62%	70%
Average gas distribution	**60%**	**70%**
Average electricity distribution	**77%**	**44%**

Source: Information disclosures, HoustonKemp analysis

The data in Table 4 above can be used to inform the ratio of revenue sensitivity between services using the ratio of income elasticities derived at section 3.2 above.

Table 5: Ratio of revenue sensitivities

Comparison of services	Ratio of income elasticity	Ratio of variable charges	Ratio of revenue sensitivity
Residential gas to residential electricity	4.67	0.78	3.65
Commercial gas to commercial electricity	0.88	1.61	1.41
Commercial electricity to residential electricity	1.73	0.57	0.98

Source: HoustonKemp analysis

Although income elasticities of demand provide indications of underlying asset betas, it is unlikely that they fully explain asset betas, even with the adjustments made above. Other factors are also likely to contribute to explaining asset betas, and these also might be expected act differently as between gas and electricity services, and as between serving residential and commercial/industrial customers. Such factors may include contractual positions, real options, operating leverage and discount rate risk.

In using these results, we account for the extent to which changes in income elasticity explain changes in asset beta by introducing a variable, θ, which captures this effect such that:

- where θ is zero, asset betas for gas and electricity supply to residential and commercial/industrial customers are all the same – ie, no factor explains any difference between them;
- where θ is one, the asset betas between gas and electricity services to different customers reflect the ratios estimated in the right hand column of 4 above; and
- values of θ between zero and one represent a region in which the ratios in Table 5 above partially, but not fully, explain differences in asset beta.

Applying the ratios from, Table 5, along with the weights from Table 3 above, to Dr Lally’s framework gives rise to the following pair of equations representing the calculation of asset betas for EDBs and GDBs respectively:

$$(0.63)\beta_{resid} + (0.37)\big(0.98\theta + (1-\theta)\big)\beta_{resid} = 0.34$$

$$(0.62)\big(3.65\theta + (1-\theta)\big)\beta_{resid} + (0.38)\big(0.98\theta + (1-\theta)\big)\big(1.41\theta + (1-\theta)\big)\beta_{resid} = \beta_{gas}$$

This system of equations can be solved to show the extent to which the asset beta for gas distribution is greater than the asset beta for electricity distribution, given a value for θ. The range of potential solutions is shown at Table 6 below.

Table 6: Asset beta differential for values of theta

Theta	Electricity beta	Gas beta	Asset beta differential
0%	0.34	0.34	0.00
10%	0.34	0.40	0.06
20%	0.34	0.46	0.12
30%	0.34	0.52	0.18
40%	0.34	0.59	0.25
50%	0.34	0.65	0.31
60%	0.34	0.71	0.37
70%	0.34	0.77	0.43
80%	0.34	0.83	0.49
90%	0.34	0.89	0.55
100%	0.34	0.96	0.62

In our view, the results in Table 6 provide empirical support for a continued asset beta differential for gas distribution services over electricity distribution services. Although it is likely that income elasticities (and revenue sensitivities) do not fully explain asset beta and so the asset beta differential is not as high as 0.62, the prior expectations of both Dr Lally and ourselves as that it is unlikely their contribution would be negligible, such that there would be zero or only a very small asset beta differential.

A1. Technical results

This appendix sets out details of the analysis that we use to estimate income elasticity of demand for gas and electricity services, including the data that we rely upon, the economic relationships that we model and the results of the methods that we apply.

A1.1 Consumption, price and income data

Table 7 below summarises the data that we compiled from MBIE, Stats NZ and the IEA.

Table 7: Description of data

Data source and data set	Annual		Quarterly	
	Range	Observations	Range	Observations
IEA				
Industrial gas price	1985 - 2014	30	1985q1 - 2015q2	122
Household gas price	1985 - 2014	30	1985q1 - 2015q2	122
Industrial electricity price	1978 - 2013	36		
Household electricity price	1978 - 2014	37		
Wholesale gas price index	1995 - 2014	20	1994q2 - 2015q3	86
Retail gas price index	1981 - 2014	34	1981q1 - 2015q3	139
Wholesale electricity price index	1995 - 2014	20	1994q2 - 2015q3	86
Retail electricity price index	1981 - 2014	34	1981q1 - 2015q3	139
Commercial gas consumption	1960 - 2013	54		
Residential gas consumption	1960 - 2013	54		
Commercial electricity consumption	1960 - 2013	54		
Residential electricity consumption	1960 - 2013	54		
MBIE				
Commercial gas price (real)	1979 - 2014	36	1979q1 - 2015q3	147
Residential gas price (real)	1979 - 2014	36	1979q1 - 2015q3	147
Commercial electricity price (real)	1979 - 2014	36		
Commercial gas consumption	1990 - 2014	25	1990q1 - 2015q3	103
Residential gas consumption	1990 - 2014	25	1990q1 - 2015q3	103
Commercial electricity consumption	1974 - 2014	41		
Residential electricity consumption	1974 - 2014	41		
Stats NZ				
Commercial gas price index			1989q1 - 2015q4	108
Household gas price index			1989q1 - 2015q4	108
Commercial electricity price index			1989q1 - 2015q4	108
Household electricity price index			1990q4 - 2015q4	101
GDP per capita (expenditure measure)	1992 - 2015	24	1991q1 - 2015q4	100
CPI	1960 - 2015	56	1979q1 - 2015q4	148

Table 7 does not include data on residential electricity prices from MBIE. Although MBIE collects these data on an annual basis, it does so for a March year, whereas all other annual data that we report above are on a calendar year basis. Given the incompatibility in these measures, we have not drawn upon MBIE's annual residential electricity price data.

We note that only MBIE's price data are provided in real, or constant price, terms. We use consumer price index (CPI) data from Stats NZ to convert our other price data sets to constant price terms. We also convert our measure of income, GDP per capita, into constant price terms using the same method.

A1.2 Models

We estimate the following models for the consumption of gas and electricity using OLS with annual data for both commercial and residential demand:

$$C_{G,t} = \alpha_G + \beta_{1,G,t}Y_t + \beta_{2,G,t}P_{G,t} + \beta_{3,G,t}P_{E,t} + \varepsilon_{G,t} \quad (1)$$

$$C_{G,t} = \alpha_G + \beta_{1,G,t}Y_t + \beta_{2,G,t}P_{G,t} + \beta_{3,G,t}P_{E,t} + \varepsilon_{G,t} \quad (2)$$

In equations (1) and (2) above:

- $C_{G,t}$ is the log of gas consumption in period *t*;
- $C_{E,t}$ is the log of electricity consumption in period *t*;
- Y_t is the log of real income in period *t*;
- $P_{G,t}$ is the log of the real gas price in period *t*;
- $P_{E,t}$ is the log of the real electricity price in period *t*;
- α_f and $\beta_{i,F,t}$ are coefficients to be estimated for variable *i* and fuel *F*; and
- ε_t are the errors.

We explain in section 3.2 above that dynamic OLS adds lead and lagged first differences of the explanatory variables to provide a robust control for issues of non-stationarity. We therefore estimate the following augmented versions of the above equations using OLS:

$$C_{G,t} = \alpha_G + \beta_{1,G,t}Y_t + \beta_{2,G,t}P_{G,t} + \beta_{3,G,t}P_{E,t} + \sum_{l=-L}^{L} \beta_{4,G,t}\Delta Y_{t-l} + \sum_{l=-L}^{L} \beta_{5,G,t}\Delta P_{G,t-l} + \sum_{l=-L}^{L} \beta_{6,G,t}\Delta P_{E,t-l} + \varepsilon_{G,t} \quad (1')$$

$$C_{E,t} = \alpha_E + \beta_{1,E,t}Y_t + \beta_{2,E,t}P_{E,t} + \beta_{3,E,t}P_{G,t} + \sum_{l=-L}^{L} \beta_{4,E,t}\Delta Y_{t-l} + \sum_{l=-L}^{L} \beta_{5,E,t}\Delta P_{E,t-l} + \sum_{l=-L}^{L} \beta_{6,E,t}\Delta P_{G,t-l} + \varepsilon_{E,t} \quad (2')$$

In equations (1') and (2'), in addition to the variables and coefficients already described:

- ΔY_{t-l} is the difference in the log of real income between period *t-l* and period *t-l-1*;
- $\Delta P_{G,t-l}$ is the difference in the log of the real gas price between period *t-l* and period *t-l-1*; and
- $\Delta P_{E,t-l}$ is the difference in the log of the real electricity price between period *t-l* and period *t-l-1*.

These models include the first difference of income for the current period (when *l* = 0), as well as *L* leads and lags of the first difference.

Finally, we estimate dynamic OLS models with quarterly data, being the above dynamic OLS models augmented with quarterly dummy variables to control for seasonal effects. We estimate these models for gas consumption only, because we do not have consumption or price data for electricity on a quarterly basis.

$$C_{G,t} = \alpha_G + \beta_{1,G,t} Y_t + \beta_{2,G,t} P_{G,t} + \beta_{3,G,t} P_{E,t} + \delta_{i,G,t} q_{i,t} + \sum_{l=-L}^{L} \beta_{4,G,t} \Delta Y_{t-l} + \sum_{l=-L}^{L} \beta_{5,G,t} \Delta P_{G,t-l} + \sum_{l=-L}^{L} \beta_{6,G,t} \Delta P_{E,t-l} + \varepsilon_{G,t} \quad (1'')$$

In equation (1'') above, in addition to the variables and coefficients already described:

- $q_{i,t}$ is a dummy equalling one in quarter *i* from the beginning of 2006 and zero otherwise, for *i = 2* to *i = 4*;[35] and
- $\delta_{i,G,t}$ is the coefficient to be estimated for dummy *i*.

A1.3 Results

In section 3.2 above we explain that we conduct tests to assess whether the variables that we use in our regressions are non-stationary. Table 8 below summarises the results of these tests for quarterly data, and Table 9 shows the results for annual data.

For each variable we conducted both an ADF test and an ADF-GLS test. We determine whether to apply a 'random walk', trend or drift specification by visual examination of the data, and report the optimal number of lags determined under the ADF-GLS test by testing down to the first significant coefficient on the last lag.

When the ADF and ADF-GLS results suggest different conclusions, we take the ADF-GLS test as providing definitive guidance due to the higher power of the test. The analysis finds that all of our data sets are non-stationary.

[35] Since we have included a constant in our model, we only include three dummies to avoid the dummy variable trap. The interpretation of the constant therefore shifts to being the base level of consumption in the March quarter, with the interpretation of the coefficients estimated for each of the dummies being the difference in base level consumption between the March quarter and quarter *i*.

Table 8: Tests for non-stationarity of quarterly data

Data set:	IEA industrial gas price	IEA household gas price	IEA wholesale gas price	IEA retail gas price	IEA wholesale electricity price	IEA retail electricity price
Specification	Random walk	Trend	Random walk	Trend	Random walk	Trend
Lags	7	6	8	11	6	12
ADF	-2.320	-3.121	-2.244	-1.304	-1.224	-3.112
Critical value	-3.505	-4.035	-2.383	-4.031	-3.539	-4.031
ADF-GLS	-2.278	-2.966	-1.898	-2.742	-1.209	-1.514
Critical value	-2.597	-3.554	-2.606	-3.533	-2.606	-3.533
Non-stationary?	Yes	Yes	Yes	Yes	Yes	Yes
Data set:	**MBIE residential gas price**	**MBIE commercial gas price**	**MBIE industrial gas price**	**MBIE industrial gas consumption**	**MBIE commercial gas consumption**	**MBIE residential gas consumption**
Specification	Drift	Drift	Random walk	Drift	Trend	Trend
Lags	10	12	0	8	8	3
ADF	-0.780	-1.239	-1.256	-1.734	-1.562	-1.758
Critical value	-2.357	-2.594	-2.615	-2.372	-4.053	-4.042
ADF-GLS	-0.875	-1.304	-1.445	-1.631	-1.194	-0.702
Critical value	-2.594	-2.358	-3.563	-2.600	-3.576	-3.576
Non-stationary?	Yes	Yes	Yes	Yes	Yes	Yes
Data set:	**Stats NZ commercial gas price**	**Stats NZ household gas price**	**Stats NZ commercial electricity price**	**Stats NZ household electricity price**	**Stats NZ GDP per capita**	
Specification	Drift	Trend	Random walk	Trend	Trend	
Lags	8	8	6	4	8	
ADF	-1.989	-1.302	-1.751	-2.509	-1.688	
Critical value	-2.369	-4.402	-3.510	-4.049	-4.060	
ADF-GLS	-1.855	-2.115	-0.697	-2.552	-1.134	
Critical value	-2.599	-3.570	-2.599	-3.579	-3.580	
Non-stationary?	Yes	Yes	Yes	Yes	Yes	

Notes: (1) The null hypothesis of the Dickey-Fuller test is non-stationarity. A failure to reject the null is therefore support for the finding of non-stationarity. (2) Critical value reported are for 0.01 level of significance.

Table 9: Tests for non-stationarity of annual data

Data set:	IEA industrial gas price	IEA household gas price	IEA industrial electricity price	IEA household electricity price	IEA wholesale gas price	IEA retail gas price
Specification	Random walk	Trend	Drift	Trend	Drift	Drift
Lags	2	8	0	0	1	2
ADF	-2.542	-3.038	-1.319	-1.716	-1.771	-1.015
Critical value	-3.736	-4.352	-2.445	-4.279	-2.602	-2.473
ADF-GLS	-2.115	-1.648	-1.267	-1.635	-1.303	-1.259
Critical value	-2.652	-3.770	-2.642	-3.770	-2.660	-1.646
Non-stationary?	Yes	Yes	Yes	Yes	Yes	Yes
Data set:	**IEA wholesale electricity price**	**IEA retail electricity price**	**MBIE residential gas price**	**MBIE commercial gas price**	**MBIE industrial gas price**	**MBIE commercial electricity price**
Specification	Drift	Trend	Random walk	Drift	Drift	Drift
Lags	0	5	0	0	0	3
ADF	-1.806	-4.789	-0.828	-2.229	-1.272	-1.886
Critical value	-2.567	-4.352	-3.682	-2.445	-2.650	-2.473
ADF-GLS	-1.846	-1.705	-0.894	-2.092	-1.212	0.120
Critical value	-2.660	-3.770	-2.642	-2.642	-2.660	-2.642
Non-stationary?	Yes	Yes	Yes	Yes	Yes	Yes
Data set:	**MBIE industrial electricity price**	**IEA commercial gas consumption**	**IEA residential gas consumption**	**IEA commercial electricity consumption**	**IEA residential electricity consumption**	**MBIE commercial gas consumption**
Specification	Trend	Trend	Drift	Trend	Trend	Drift
Lags	0	8	9	7	7	8
ADF	-3.034	-0.957	-2.663	-5.151	-9.599	-2.057
Critical value	-4.288	-4.196	-2.445	-4.187	-4.187	-3.143
ADF-GLS	-1.997	-1.384	-1.824	-0.744	-1.877	-1.598
Critical value	-3.770	-3.755	-2.618	-3.755	-3.755	-2.660
Non-stationary?	Yes	Yes	Yes	Yes	Yes	Yes
Data set:	**MBIE residential gas consumption**	**MBIE commercial electricity consumption**	**MBIE residential electricity consumption**	**Stats NZ GDP per capita**		
Specification	Drift	Trend	Trend	Trend		
Lags	0	8	8	6		
ADF	-2.246	-1.681	0.062	-0.916		
Critical value	-2.508	-4.316	-4.316	-4.380		
ADF-GLS	-1.329	-0.644	-1.631	-2.455		
Critical value	-2.660	-3.770	-3.770	-3.770		
Non-stationary?	Yes	Yes	Yes	Yes		

We explain in section 3.2 above that we conduct tests for cointegration of the relationships that we estimate in each of the models sets out above. We report the results of Engle and Granger tests in Table 10 below. These tests indicate that we can place greater reliance on the results of the models that we estimate on our quarterly data. We note that the power of the test is limited in small samples. It may therefore be difficult to reject the null hypothesis of no cointegration in tests on our annual data.

Table 10: Engle and Granger tests for cointegration

Model:	Residential gas – annual	Commercial gas - annual	Residential electricity - annual	Commercial electricity - annual	Residential gas - quarterly	Commercial gas - quarterly
Test statistic	-3.848	-3.856	-3.175	-4.729	-5.791	-5.144
10% critical value	-4.200	-4.219	-4.200	-4.200	-4.858	-4.858
5% critical value	-4.630	-4.656	-4.630	-4.630	-5.182	-5.182
1% critical value	-5.545	-5.591	-5.545	-5.545	-5.821	-5.821
Cointegrated?	No	No	No	Yes, at 5%	Yes, at 5%	Yes, at 10%

Table 11 below sets out the results of OLS and dynamic OLS regressions estimated using annual data, while Table 12 shows the results of dynamic OLS regressions estimated using quarterly data. We present the data sources that we use in these regressions, alongside the coefficients and p-values for each. For each regression, we also report the adjusted R^2.

Table 11: Models of New Zealand energy demand estimated with annual data

	C_G or C_E	Y	P_G	P_E	Adjusted R^2
OLS models					
Residential gas demand	MBIE	Stats NZ	MBIE residential	IEA household	
Coefficient estimate (P-value)		3.61 (0.000)	-0.40 (0.041)	-1.27 (0.032)	0.822
Commercial gas demand	IEA	Stats NZ	IEA industrial	IEA industrial	
Coefficient estimate (P-value)		1.39 (0.000)	-0.24 (0.038)	0.08 (0.829)	0.746
Residential electricity demand	MBIE	Stats NZ	MBIE residential	IEA household	
Coefficient estimate (P-value)		0.80 (0.000)	0.03 (0.355)	-0.20 (0.156)	0.936
Commercial electricity demand	MBIE	Stats NZ	MBIE commercial	MBIE commercial	
Coefficient estimate (P-value)		1.37 (0.000)	0.18 (0.001)	0.10 (0.251)	0.985
Dynamic OLS models					
Residential gas demand	MBIE	Stats NZ	MBIE residential	IEA household	No leads/lags
Coefficient estimate (P-value)		3.84 (0.000)	-0.38 (0.018)	-1.54 (0.005)	0.813
Commercial gas demand	IEA	Stats NZ	IEA industrial	IEA industrial	No leads/lags
Coefficient estimate (P-value)		1.25 (0.003)	-0.44 (0.029)	0.47 (0.441)	0.828
Residential electricity demand	MBIE	Stats NZ	MBIE residential	IEA household	1 lead/lag
Coefficient estimate (P-value)		0.82 (0.000)	0.06 (0.025)	-0.27 (0.003)	0.985
Commercial electricity demand	MBIE	Stats NZ	MBIE commercial	MBIE commercial	No leads/lags
Coefficient estimate (P-value)		1.42 (0.000)	0.15 (0.042)	0.16 (0.038)	0.988

Notes: (1) P-values are calculated using Newey-West standard errors. (2) Dynamic OLS models with no leads or lags include first differences of explanatory variables.

Table 12: Models of New Zealand energy demand estimated with quarterly data

	C_G or C_E	Y	P_G	P_E	R^2
Dynamic OLS models					
Residential gas demand	MBIE	Stats NZ	MBIE residential	IEA retail	5 leads/lags
Coefficient estimate (P-value)		4.18 (0.000)	-1.40 (0.000)	-1.27 (0.064)	0.791
Commercial gas demand	MBIE	Stats NZ	MBIE residential	Stats NZ	5 leads/lags
Coefficient estimate (P-value)		1.62 (0.000)	-0.11 (0.478)	-0.83 (0.002)	0.826

Note: (1) P-values are calculated using Newey-West standard errors.

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