



Effects of vertical integration on capacity bidding behaviour

A REPORT PREPARED FOR HERBERT SMITH FREEHILLS

August 2017

This document is protected by legal professional privilege.

Effects of vertical integration on capacity bidding behaviour

Executive summary	1
1 Introduction	4
2 Statistical testing	6
2.1 Method and data	6
2.2 Results	14
3 Interpretation of results	18
APPENDIX: REGRESSION ANALYSIS EXPLAINED	22
Regression analysis	22
Assessing the estimated model and coefficients	28

Effects of vertical integration on capacity bidding behaviour

Tables

Table 1: Correlation between key explanatory variables	14
Table 2: Regression results from various model specifications	21

Figures

Figure 1: Average Bidding Index throughout the NEM	9
Figure 2: Herfindahl-Hirschman index	11
Figure 3: Reserve plant margin	12
Figure 4: Index of vertical integration in the NEM	13
Figure 5: Plot of engine power vs efficiency	23
Figure 6: Least squares regression line for how engine power affects efficiency	25
Figure 7: Plot of engine power vs weight	26
Figure 8: Engine power vs efficiency, by transmission type.	27
Figure 9: Regression output for estimated equation (6)	28

Executive summary

1 Governments, regulators and consumers are keen to understand the causes of electricity price rises. Many potential causes have been identified in the recent public debate, including:

- Closures of old generators
- Declining reliability of old generators
- Declining operation of older, less flexible generators as more intermittent, subsidised renewable generators take greater market share
- Rising fuel costs, and in particular for gas generators.
- Lack of investment in new generators due to uncertainty about carbon pricing
- Horizontal mergers
- Vertical mergers

2 Given the multitude of potential causes of rising wholesale prices it seems improvident to attribute the cause solely or primarily to any one of these factors without any well founded analysis.

3 Frontier Economics has been asked to examine the contribution of vertical integration between generators and retailers to the bidding behaviour of generators that are vertically integrated and on the market generally.

4 In particular we have been asked to test whether vertical integration causes vertically integrated generators to bid more capacity at higher prices or choose to make more plant unavailable where:

- **Bidding higher** refers to the practice in the NEM where generators make their plants available for dispatch but at relatively high prices. This is allowed under the NEM rules and is an important design feature of the pro-competitive ‘self commitment’ design of the NEM where generators decide when they are dispatched by how they bid. Generators make themselves available to be dispatched and bid a price equal to what they consider to be the opportunity cost of being dispatched, which also reflects the risks of managing scarce fuel (in particular gas) and their ability to recover their start-up costs; and
- **Less availability** refers to practice of generators not making their plants available for any price. This physical withdrawal of capacity could be for maintenance purposes or because the surpluses of capacity means that it is not worthwhile for a generator to bear the costs of keep a generator available for production.

Collectively, we refer to any changes in bidding behaviour as **Bidding Changes**.

5 To test whether and the extent to which vertical integration has contributed to Bidding Changes we have used statistical techniques to help tease out the effects

of different factors that are claimed to be important determinants of bidding behaviour and, hence, prices.

- 6 We found that the most important contributor to a change in bidding behaviour that causes prices to rise was the declining quantity of reserve generation capacity in the NEM.
- 7 Reserve generation capacity is essential to the secure and reliable operation of a power system. Spare capacity is used to supplement supplies when power stations cannot run because of technical faults or maintenance or because of limitations on the grid prevent power stations from being dispatched.
- 8 This decline in reserves has occurred because a large quantity of less utilised, older coal fired generators that used to provide base load power have been shut down and not replaced with new base load generators. This means that the expensive-to-run power stations that are kept in reserve are now running more often and setting higher prices. It also means that other generators reflect the scarcity of spare capacity by bidding higher prices, which is how the NEM was designed to operate. The higher prices would normally cause investors to build more base load generators to capture a share in the increased profits that exist while there is a shortage of spare capacity. However investors are no longer responding to NEM prices in the way they used to.
- 9 This change in investor behaviour is due to the high level of uncertainty surrounding carbon pricing and the fact that the Federal government's Renewable Energy Target is subsidising renewable generation capacity that is continuing to displace existing base load generation.
- 10 In this environment no base load generation investment is viable unless it is supported in the long term by the government. This is because there is no base load generation investment that is viable both with and without a carbon price (at least a carbon price sufficient to achieve Australia's Paris commitments) and investors expect that some form of carbon pricing is highly likely to apply at some point over the life of an investment. In the face of such risk, investors are waiting for resolution on carbon pricing and/or waiting for prices to reach a high enough level to justify taking the higher investment risk.
- 11 As part of the statistical model we simultaneously examined the influence of other key factors such as horizontal and vertical integration. In particular we test whether these factors are statistically related to bidding more capacity at higher prices or physically withdrawing more capacity from the market. More specifically we test whether generators are bidding a greater share of capacity either above \$300/MWh, which is the conventional 'cap contract' price used in the NEM which delineates between peak and non-peak prices, or not at all.
- 12 We found that vertically integrated generators in fact behave more competitively on average than when they were operating as stand-alone generators. The vertically integrated generators were found to be bidding 4 to 6 percentage points more

capacity at competitive prices. This statistically significant, robust, and striking result is contrary to claims that vertically integrated generators will bid at higher prices than stand-alone generators.

- 13 We could not find any statistical evidence that the trend towards vertical integration across the market was contributing to generators bidding at higher prices, and nor could we find any compelling statistically significant evidence that horizontal integration was causing generators to bid more capacity at higher prices.
- 14 The following report describes the statistical techniques and data used in the study and provides greater insights in the modelling results.

1 Introduction

15 Frontier Economics has been asked by Herbert Smith Freehills, lawyers for AGL, for our opinion of the effects of increasing vertical integration between electricity generators and retailers on wholesale electricity prices in Australia. We have been asked to address the following question: Has vertical integration (VI) led to: material changes in:

- bidding
- contracting behaviour by generation plant now owned by AGL (i.e. Loy Yang A and Macquarie Generation).

16 In *Australian Gas Light (ACN 052 167 405) v ACCC (No 3)* (2003) ATPR 41 966 (first AGL case), the Commission's hypothesis concerning the link between VI and wholesale prices principally arose from the fact that vertical integration would provide AGL as a retailer with a 'natural' hedge. This hedge would reduce AGL's requirement for protection from wholesale price volatility by means of financial hedges. The reduction in AGL's demand for financial hedges would result in a corresponding *pro rata* reduction in the hedge contracts signed by base load generators in Victoria. This would in turn increase the proportion of Victorian generators' outputs exposed to the wholesale spot price, thereby raising their incentives to engage in high bidding or offering less plant availability.¹

17 In *Application for Authorisation of Acquisition of Macquarie Generation by AGL Energy Limited* [2014] AComT 1 (25 June 2014) (second AGL case), the Commission's concern with the link between VI and wholesale prices was principally that vertical integration would increase the incentive for a generator to raise wholesale prices to eliminate competitor retailers – through a 'vertical squeeze'.²

18 The ACCC's concern in both cases was with the market as a whole (as distinct from concern with the behaviour of AGL). The effect of VI on bidding by the generators owned by AGL is likely to be the same as the effect of VI on the bidding of all gentailers. For this reason, we chose to analyse the effects of VI on bidding by generators as a whole rather than to confine our attention to bidding by the generators owned by AGL.

19 Frontier Economics advised solicitors for AGL in relation to both cases. In relation to the second case, the submission made on behalf of AGL noted that a VI business's incentives with respect to the bidding of its generation plant depended on the extent to which the entity as a whole was positively ('long') or

¹ See First AGL case, paras 357 and 502.

² Second AGL case, para 23.

negatively ('short') exposed to the wholesale spot price. AGL's submission stated that:³

If AGL's generation is dispatched, that generation provides a natural hedge for a corresponding portion of AGL's retail load. If AGL's generation is not dispatched, AGL does not have any such natural hedge for that portion of its retail load, and as well as foregoing the revenue from the Pool Price in relation to that load, AGL must acquire electricity in the NEM at prevailing Pool Prices in order to satisfy its retail obligations. This trade-off, and the cost and risk associated with AGL's generation not being dispatched, currently constrains AGL when it bids generation into the NEM, and will continue to constrain AGL if AGL acquires Macquarie Generation.

20 The economic evidence in the two AGL cases consisted principally of simulation models and arguments from economic theory. However, the increased VI of the past 15 years has enabled us to use market data to statistically test whether this increased VI has led to high bidding or offering less plant availability. This Report presents the results of this statistical analysis.

³ AGL Energy Limited, *Proposed Acquisition of Macquarie Generation, Application to Australian Competition Tribunal – Form S*, 24 March 2014, para 10.12.

2 Statistical testing

2.1 Method and data

21 We used statistical regression analysis to test the hypothesis that increased VI has led to Bidding Changes. We also statistically accounted for other factors that may have influenced generator bidding. We sought a dependent variable (left hand side or LHS) with which to capture generator bidding. The dependent variable we settled on was based on the ratio of capacity that was bid ‘genuinely’ to total available capacity.⁴ There were two independent or explanatory (also known as right hand side or RHS) variables of principal interest, both related to VI. We considered the overall extent of VI throughout the market, but also whether the owner of an individual plant was vertically integrated or not. We also controlled for:

1. The extent of horizontal concentration of the generation sector using the Herfindahl-Hirschman Index (HHI);
2. The extent of supply shortage or surpluses across the NEM, measured as the ratio of the total capacity of the NEM to the maximum demand of the NEM in a year;⁵
3. The type of generator, captured by the type of fuel used by the generator;
4. The state in which the generator was located;
5. A variable to control for time.

The variables used in the models are explained more fully below.

⁴ While for some regressions the dependent variable is the fraction of capacity that is genuinely offered, in some specifications the variable is binary: for example if more or less than 50 percent of capacity is genuinely offered.

⁵ Power systems need generation capacity in reserve to account for planned and unplanned outages of generators to ensure continuity of supply. The NEM comprises a range of power generators which differ in their fixed and variable costs. In general, generators that have high fixed costs tend to have low operating costs and these are suited to base load operation. Other generators have relatively low fixed but high operating costs, for example gas fired generators. These types of generators are more suited to minimal intermediate and peak load operation. The NEM is primarily supplied by base load thermal generators and renewable power supplies. As older base load generators are being progressively shut down the more expensive intermediate and peaking type generators are operating more and, therefore, setting the wholesale price at their higher cost more often.

2.1.1 Unit of observation

22 Given we are interested in the relationship between VI and bidding behaviour we use generator bids for the basis of our dependent variable.

23 The primary data for this investigation were the bids submitted by distribution units (DUs - generators) to AEMO. These bids were aggregated within a power station so that our unit of observation is an individual power station. We did not aggregate power stations because we expected that the characteristics of power stations were likely to play a substantial role in the decision to make capacity available.⁶

24 We observed bidding data for 30 minute trading intervals. However, our explanatory variables of interest, those related to vertical integration, and other market characteristics, were obtained in a quarterly format. Accordingly, we aggregated all trading periods within a quarter. The data consist of observations from the final quarter of 2003 to the final quarter of 2016.

2.1.2 Total bid capacity

25 Our bidding data were derived from AEMO's bidding data by generating unit. These data contained the price and quantity bands per half hour as well as any re-bidding that occurred. We used these data to determine the bids that were submitted.⁷ We counted as 'genuine bids' (i.e. not high price bids or bidding less availability) only those at or below \$300/MWh. This number was chosen as it is regarded as a traditional strike price for cap contracts, and may be used as an objective measure. This price has not changed in nominal terms, so there was no need to increase it over time. Accordingly, capacity bid at prices above \$300/MWh was regarded as a 'high bid'.

26 It is important to note that we do not consider offering capacity at a price greater than \$300 as inappropriate. Indeed, the NEM energy-only design would simply not work in terms of encouraging new investment unless there were sufficient periods of prices higher, or expected to be higher, than \$300/MWh. Rather, we consider this pricing threshold as an appropriate measure to use in a statistical investigation of the impact of vertical integration on bidding behaviour.

27 In addition to this high bidding we also took account of bidding that reduced the capacity being offered to be dispatched – bidding less availability. We sought a measure of capacity that could not reasonably be considered to be affected by a strategic decision by a generator to make less capacity available to the market. For

⁶ It would be unfair to compare bidding behavior of a firm that owns peaking generators to that of a firm that owns base load generators.

⁷ For AEMO data that are currently available, see http://www.nemweb.com.au/REPORTS/CURRENT/Yesterdays_Bids_Reports/

this reason, we chose to use a capacity measure that reflected the total physical capability of plant in existence at a point in time, even though some of it may not be available at any given time due to outages for necessary maintenance or repairs.⁸ We took this approach on the (highly conservative) assumption that there is no objective way of distinguishing between capacity not bid available for necessary maintenance and strategic withdrawals.⁹ This had the consequence that capacity not bid available for legitimate maintenance purposes was treated as if it was bid this way strategically.

28 In terms of the measure used to take account of bidding less availability, capacity may genuinely not be available due to maintenance or other technical reasons. Capacity may also not be made available if generators expect demand to be low enough in the trading period (on the basis of predispatch information¹⁰) to not warrant starting a generator. Indeed, start-up costs for open cycle gas turbines¹¹ in particular play a large role in determining when capacity will be made available.¹²

29 The objective of this statistical modelling exercise was to test the hypothesis that increases in VI led to Bidding Changes, so the dependent variable in our analysis – the variable we were seeking to explain – is the fraction of a power station’s capacity that is bid high (above \$300/MWh) or unavailable. We term this measure as the Bidding Index (BidIndex).

As can be seen below in

⁸ The capacity of the relevant assets was derived from AEMO’s ‘Generation Information’ publications.

⁹ We did not include mothballed and retired capacity in our capacity measures.

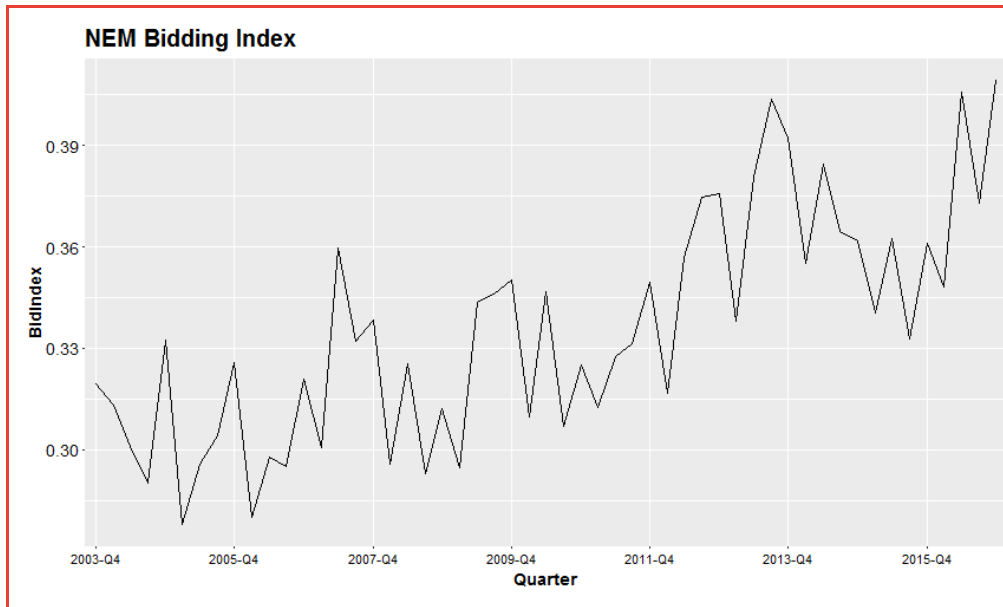
¹⁰ Subject to change due to demand conditions and rebidding.

¹¹ In addition to the issues regarding gas contracts that may be acquired prior to dispatch to reduce price gas price risk.

¹² It is important to note that a generator may initially bid above \$300/MWh to provide them with the opportunity to be dispatched and then rebidding to a lower price if market conditions are likely to produce a price that meets a generators risk adjusted opportunity cost. However if market conditions remain unsuitable for this generator they may leave the bid standing. Thus this will appear as a generator bidding high, even though it may have been made available if conditions were suitable.

- 30 Figure 1, the share of capacity that is bid high or made unavailable has tended to increase over the past decade. Over the same period VI has also increased, which could cause some to prematurely conclude that VI *causes* Bidding Changes. The aim of this study was to rigorously examine whether Bidding Changes can be statistically attributed to VI and, if so, the extent to which VI is responsible for the Bidding Changes.

Figure 1: Average Bidding Index throughout the NEM



Source: Frontier Economics analysis

2.1.3 HHI

31 In the Cournot quantity-bidding model, the quantity offered by firms is related to market concentration. That is, in general, in a market dominated by a small number of large firms, these firms have a stronger incentive to withdraw capacity because they can drive the price up enough to make up for the loss of market share. Cowling and Waterson showed that, if suppliers have differing marginal costs, the measure of concentration relevant to the Cournot model is the Herfindahl-Hirschman index (HHI).¹³ Of course, in applying such economic models, it is important to take account of the market in which firms operate, and hence how prices are set, their cost structures and hence the extent of entry and exit barriers, and the risks of engaging in any attempt to withdraw capacity to raise prices. Notwithstanding these limitations of the standard Cournot model, we used the HHI as a control variable in the statistical model. This will help isolate the effect of horizontal integration from vertical integration.

32 While market shares used to calculate the HHI are generally based on revenue, we calculated the market shares used for our HHI based on capacity data. Market

¹³ K Cowling and M Waterson, "Price-Cost Margins and Market structure", *Economic Journal*, Vol 43 (1976) pp 249-274. For a textbook exposition, see Massimo Motta, *Competition Policy, Theory and Practice*, Cambridge University Press (2004) pp 123-124.

shares based on capacity are often used to determine the HHI in markets for homogeneous products.¹⁴

33 The AER's annual 'State of the Energy Market' report classifies ownership of generation assets according to which entity has trading rights, rather than ownership of the plant. We use this data to attribute bidding control to power stations. AEMO's 'Generation Information' publications occur approximately quarterly and includes data on the capacity of power stations that we use in this analysis. The HHI series is therefore a quarterly time series, applying to the NEM as a whole.

34 As seen in Figure 2, the HHI has increased since 2010. However it is important to put this rise in HHI into context. For example, the US Department of Justice and Federal Trade Commission classify market competitiveness into the following three categories according to the value of the HHI:

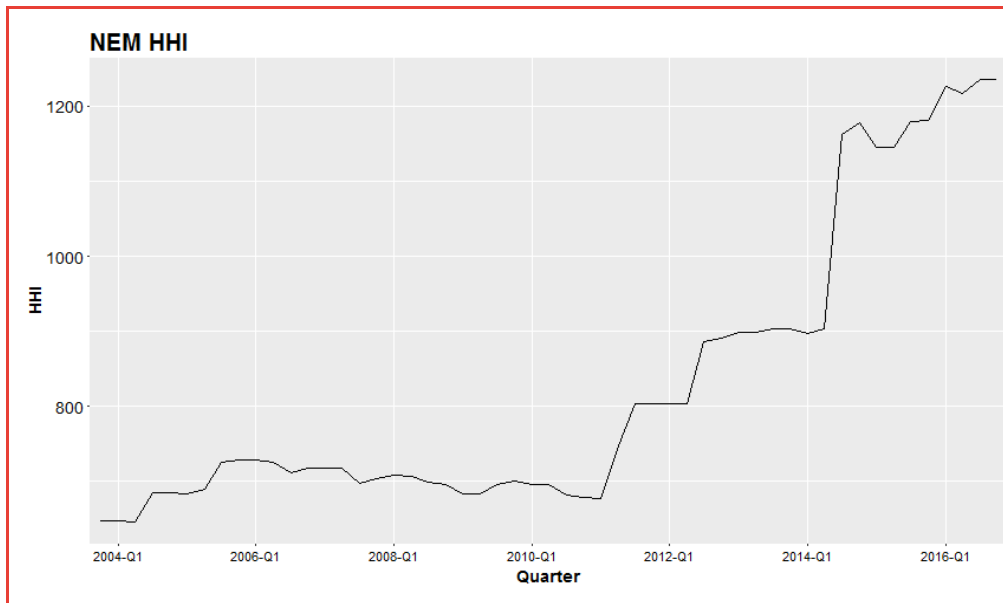
- Unconcentrated Markets: HHI below 1500
- Moderately Concentrated Markets: HHI between 1500 and 2500
- Highly Concentrated Markets: HHI above 2500.

According to these measures, the NEM falls firmly in the "unconcentrated" category, even after recent generation mergers.¹⁵

¹⁴ U.S. Department of Justice and the Federal Trade Commission, *Horizontal Merger Guidelines*, August 19, 2010. P 17.

¹⁵ Para 7.14 of the ACCC Merger Guidelines states that the ACCC will generally be less likely to identify horizontal competition concerns when the post-merger HHI is less than 2000. The NEM has a HHI well below this threshold.

Figure 2: Herfindahl-Hirschman index



Source: Frontier Economics analysis

2.1.4 Generator type

35 The generator type is highly relevant to bidding decisions, as costs and responsiveness can differ greatly depending on whether a generator is a base load or a peaking plant. Generators are classified as one of eight types according to the type of fuel used.¹⁶

2.1.5 Region

36 Although our analysis examined the NEM as a whole, the region in which a generator was located/operated was included as a control variable to allow the potential for the incentive to engage in different bidding behaviour across the NEM regions, reflecting the market conditions by region.

2.1.6 Reserve plant margin

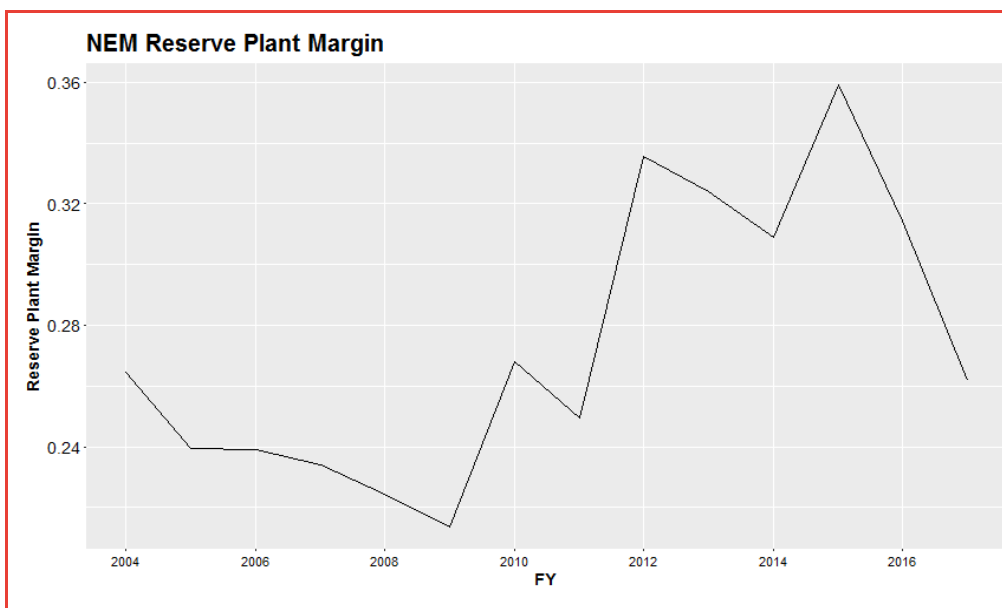
37 It is well-known that Cournotesque incentives to bid higher when demand is close to supply capacity – indeed, that is an essential design feature of the NEM.¹⁷ Accordingly, we construct a variable measuring the amount of capacity in reserve, in excess of demand. This measure is an annual measure, and is equal to $(Capacity_t - MaxDemand_t)/Capacity_t$.

¹⁶ The types used were: black coal, brown coal, gas, hydroelectric, liquid fuel, solar, wind, and other.

¹⁷ See Jean Tirole, MIT Press (1988) pp 228-234.

38 In this equation, capacity is the capacity of the NEM as a whole and MaxDemand is the maximum observed demand of the system in a financial year. Accordingly this is an annual time series.¹⁸ As shown in Figure 3, the reserve plant margin averages around 30%. However, it has changed considerably throughout the modelling period; while the margin rose between 2009 and 2015 it has since fallen considerably. This supply shortfall has been caused by the closure of older, large scale generators which have not been replaced by any new thermal generators. The only significant investment in new generation in the NEM has been subsidised renewable generators that do not supply power on demand, only when the wind blows or the sun shines.

Figure 3: Reserve plant margin



Source: Frontier Economics analysis

2.1.7 Owner VI dummy (OwnerVI)

39 In this study, we tested the hypothesis that increased VI has led to Bidding Changes. Accordingly we created a dummy variable, equal to 1 if the owner of the generator station was vertically integrated, and 0 if not. As ownership status¹⁹ of generators was obtained quarterly, this variable is also a quarterly series. It is also important to correctly classify a generating firm as vertically integrated or not, as some generators may hold retailer licenses to sell directly to large customers yet would not be considered vertically integrated (for example CS Energy).

¹⁸ Financial year basis.

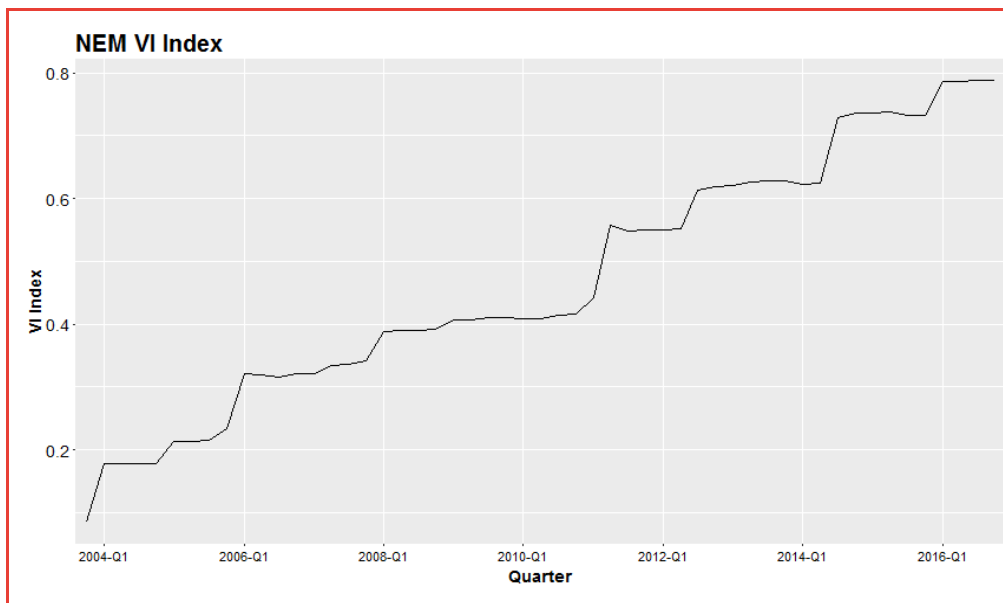
¹⁹ This is based on trading rights reported to AEMO, as above.

40 It is important to note that this is a binary variable. Because we could not obtain the necessary data, we did not attempt to take account of the degree to which a firm was vertically integrated.

2.1.8 Vertical integration index (MarketVI)

41 As noted above, the purpose of our analysis was to test the hypothesis that increased vertical integration led to Bidding Changes. Accordingly we created a measure of the degree of vertical integration in the market. This measure gives the proportion of generation capacity²⁰ held by vertically integrated generator firms in each quarter (see Figure 4). It is this rise in VI which also reflects the rise in more capacity being bid into the market at higher prices that causes some to conclude VI is the cause of higher prices. However, mere correlation does not imply causation. The statistical model is used to test whether VI is a driver of higher prices and to what extent.

Figure 4: Index of vertical integration in the NEM



Source: Frontier Economics analysis

²⁰ Defined as previously.

2.2 Results

2.2.1 Correlation of time series variables

42 Three of the key explanatory variables used in our analysis are the HHI of the generation sector, the index of vertical integration throughout the market (MarketVI), and the reserve plant margin which measures the proportion of capacity exceeding maximum demand (ReserveMargin). An additional variable that may be included is a time trend to capture the effects of other conditions that may change over time.²¹

43 These four variables vary across time and are highly correlated with each other as seen in Table 1. Of particular note is the high correlation between Market VI and the time trend.²²

Table 1: Correlation between key explanatory variables

	MarketVI	HHI	ReserveMargin	Time
MarketVI	1			
HHI	0.895	1		
ReserveMargin	0.723	0.665	1	
Time	0.986	0.867	0.715	1

Source: Frontier Economics analysis

These correlations underline why it is highly inappropriate to make conclusions based on pairwise correlations between the Bidding Index (BidIndex), as seen in

²¹ This is expressed as the number of quarters since an arbitrarily chosen start date. The start date is irrelevant and is chosen without loss of generality.

²² Although we consider and estimate models that omit the time trend, this has a possible effect of attributing to Market VI the effect of other variables that change steadily over time. Such unobserved variables could include the increased importance of renewable generation, as wind and solar are not able to consistently provide electricity. This could result in an increased ability of other generators to bid higher or less availability.

Figure 1, and variables such as HHI or MarketVI, as seen in Figure 2, Figure 3 and Figure 4. To attribute Bidding Changes to HHI based on such a superficial analysis implicitly assumes that other variables do not matter, a highly inappropriate assumption. It is even inappropriate to only consider these four variables to affect bidding; the types of generation plants that supply the NEM changes over time and would need to be accounted for. While the MarketVI index may be positively correlated with the NEM-wide BidIndex, the relationship must withstand scrutiny via regression analysis before any conclusions regarding causality should be even considered.

44 These strong correlations also suggest that the analysis may suffer from the econometric issue of ‘multicollinearity’, which tends to make estimates regarding the effects of the individual variables less reliable than would otherwise be the case. In particular, it becomes challenging to make definitive statements regarding the effect of variables that exhibit a strong degree of interconnectedness. The ability of regression analysis to quantify the patterns in the data becomes limited as the patterns become more entangled. In the extreme case, where two explanatory variables change in exactly the same manner, it becomes impossible to disentangle the individual effects.²³ While that is not the case here, the fact remains that the nature of the data obscures the true effect of these variables.²⁴

2.2.2 Regression model

45 We commenced the analysis by examining the relationship between BidIndex and the key explanatory variables using the method of ordinary least squares. The dependent variable, the variable we are trying to explain, is the average proportion of capacity that is not offered at a price of \$300 or less by a station over a quarter. The base model estimated was:

$$46 \quad BidIndex_{it} = \beta_1 + \beta_2 MarketVI_t + \beta_3 OwnerVI_{it} + \beta_4 HHI_t + \beta_5 ReserveMargin_t + \beta_6 t + \beta_7 Capacity_{it} + Region_i' \gamma + Type_i' \delta + \varepsilon_{it}$$

47 We first ran the full model, then omitted control time series variables over the course of multiple specifications in order to check the robustness of our findings.²⁵ We also considered a number of alternative regression models.²⁶ We repeated these

²³ Impossible without making additional (often unreasonable) assumptions.

²⁴ The reserve plant margin however is less correlated with the other variables as seen in Table 1, to the extent that we can be more definitive regarding the effect of reserves on bidding behaviour.

²⁵ We perform the regression with all variables in the specification, and three variants with each of HHI, ReserveMargin and time omitted, as well as two variants with time and either HHI or ReserveMargin omitted. We repeat this excluding Market VI and subsequently Owner VI.

²⁶ Logit models where the dependent variable is 1 if any capacity not offered at \$300/MWh; logit models where the dependent variable is 1 if less than half capacity is offered at \$300/MWh; fractional logit models where the fitted dependent variable is constrained to be between 0 and 1; and fixed effects

exercises for specifications where the OwnerVI variable is omitted, and alternatively where MarketVI is omitted.²⁷

- 48 The HHI of the NEM showed a positive and statistically significant²⁸ effect in a number specifications, yet in other specifications no statistically significant effect was observed: there is a lack of consistency or robustness. This result is therefore ambiguous – it cannot be concluded that horizontal integration is or is not making a statistically significant contribution to rising prices. This result most likely reflects the fact that the NEM is considered to be “unconcentrated” even though there has been a rise in the level of concentration.
- 49 The statistical models show that reserve plant margin is a significant explainer of BidIndex: that is, as the level of spare capacity declines less capacity is offered at a price of \$300/MWh or less, a change that would generally increase prices. This was expected, and is consistent with the notion that generators are more able to bid high or offer less availability to raise prices when the demand-supply balance of the market is tighter. The size of this effect is substantial: the 10 percentage points fall in the reserve plant margin from 2015 to 2017 is estimated to account for a 5 percentage points increase in the BidIndex of generators.
- 50 Turning to the effect of the vertically-integrated status of the individual power stations, we observed that the effect of OwnerVI on BidIndex was *consistently negative and highly significant*, typically exceeding the 1% level of statistical significance, meaning that vertically integrated generators bid more capacity at less than \$300/MWh. The size of the coefficient implies that a power station that is owned by a vertically integrated firm will *decrease* the BidIndex by 4 to 6 percentage points, implying that *more* capacity will be offered to the market below \$300.²⁹ This is a substantial effect. This pro-competitive effect of OwnerVI is therefore both statistically and practically significant.
- 51 The effect of the level of vertical integration across the market on BidIndex is less clear.³⁰ The coefficient is statistically significant only when we did not allow for a

panel models of linear and other models, allowing each station to have a fixed effect on its bidding behaviour.

²⁷ Regression results of a number of specifications are included in Table 2. The estimates for the effect of station fuel type, region, and intercepts are omitted for brevity.

²⁸ Robust standard errors were used to perform significance tests, with the exception of the fixed effects models, which used clustered standard errors (clustered at the power station level). Fixed effects logit models used the default standard errors (original information matrix).

²⁹ As seen in Table 2 the effect was a decrease of 4 percentage points in the OLS models, 5 percentage points in the fixed effect linear model. The estimated decrease in the fractional logit regression is 6 percentage points (marginal effect taken at means).

³⁰ Whilst controlling for the vertical integration status of the individual generator.

time trend.³¹ While the sign tended to be positive (that is, market-wide VI is associated with a higher BidIndex Bidding Changes), there were a number of specifications where an increase in vertical integration in the NEM was associated with a *decrease* in high bidding and capacity unavailability.

52 The statistical significance and sign of the market-wide VI variable depended primarily on whether or not a time trend variable was included in the regression, as the share of capacity controlled by vertically integrated firms tended to increase uniformly over time (as seen in Figure 4). If the time trend was removed, the effect of the market-wide VI variable was quite often statistically insignificant when positive and occasionally negative and statistically significant. Accordingly, we find no robust effect of market-wide VI. Beyond that, a positive coefficient on the extent of vertical integration throughout the market would be difficult to reconcile with the finding that a station owned by a vertically integrated firm would bid more competitively. This would imply that vertical integration throughout the market is associated with a higher BidIndex of power stations that are not controlled by vertically integrated firms.

³¹ It is significant at the 5% level when the time trend is omitted, and significant at the 1% when both the time trend and HHI are omitted. As HHI would be considered to be a relevant variable it would be inadvisable to hold the latter result in high regard, especially as HHI and MarketVI are highly correlated, as seen in Table 1. The sign is positive in both cases.

3 Interpretation of results

53 The result that the vertically integrated generators in the NEM behave more competitively is consistent with the facts and the economics that arise from those facts. To understand why this modelling result makes economic sense it is important to first understand the ‘theory of harm’ that is the basis for concerns about vertical integration.

54 Opponents of vertical integration say that stand-alone generators have a stronger incentive to bid more competitively than vertically integrated generators. They maintain this belief because generators use financial hedging contracts to manage their revenue volatility. These contracts require generators to pay to the counterparty (usually retailers) the difference between the contract strike price and the prevailing spot price. If the generator offers less capacity available to the market in order to raise the spot price above the strike price of any hedging contracts the generator has to pay the excess costs back to the counterparty. Opponents of vertical integration consider these hedging contract payments undermine the incentive of generators to drive up the spot price.

55 In the 2014 Macquarie Generation case in the Australian Competition Tribunal the ACCC advanced this theory of harm by stating that when a generator merges with a retailer they no longer need these financial hedging contracts to manage spot price and revenue risk. This is because when a vertically integrated retailer is paying a high spot price for electricity its affiliated generator is earning the same high spot price. This is called a ‘natural hedge’. The ACCC was concerned that the operation of a natural hedge resulting from vertical integration weakens the discipline on generators to bid competitively as the generator no longer face the loss of revenues above the contract strike price.

56 However, this vertical integration theory of harm fails to take account of the financial properties of the fixed price retail contracts vertically integrated retailers almost invariably have with their customers. Fixed price retail contracts create the same cash flows for the integrated business as generator wholesale contracts do for stand-alone generators. For example, if a vertically integrated generator raises the wholesale price above the wholesale cost embodied in a retail contract with a customer the retail arm loses money because it costs more to buy power than the price they sell to customers. That is, the loss to the retail arm is the same as the contracting losses suffered by the stand alone generator. To the extent the contract payments deter stand-alone generators from raising spot prices, the financial loss faced by the retail arm of a vertically integrated business will create the same incentive.

57 With the above in mind, vertical integration in the NEM has tended to involve large retailers acquiring the largest base load generators (e.g. Origin acquiring Eraring, AGL acquiring Loy Yang A and Macquarie Generation). In general and ignoring risk, large generators have a greater ability and incentive to bid high and

offer less availability as they can derive greater benefit from offering less capacity to the market because even at a reduced level they continue supply a large amount of electricity to the market. Given the large retail loads that are being supported by these vertically integrated generators they are generally more naturally hedged after the vertical merger than they were financially hedged before the vertical merger.

58 Another factor that could explain this more competitive behaviour is that stand-alone generators know precisely their contracted positions and bid to that position while vertically integrated generators who have to cover an unknown position (because retail load is not known until usually well after the trading interval) are more likely to act conservatively and bid more capacity at lower prices.

59 Given the modelling shows that the vertically integrated generators are behaving more competitively, it might be expected that the modelling would also show a similar result regarding the relationship between market vertical integration and the Bidding Index of stations. However, we could not find any statistically significant relationship between the extent of vertical integration across the NEM and BidIndex.

60 This paradoxical modelling result for market vertical integration is consistent with expectations.

61 If retailers who vertically integrate switch their hedging from financial hedges with multiple generators to physical hedging with their own (large) generators, it must mean that the overall level of hedging (natural and financial) does not change. This implies that the power stations that formerly supplied financial hedges to now vertically integrated retailers are less hedged after vertical integration occurs. These more lightly hedged generators are likely to have stronger incentive to engage in high bidding and offering less availability (for the reasons suggested by the ACCC), thereby offsetting the more competitive behaviour by the now vertically integrated generators.

62 Given the modelling suggests that vertical integration is not the cause for recent price rises the question remains: what does, logically and statistically, have the potential to explain price rises?³²

63 The modelling included measures of the extent of horizontal concentration of the generation sector as well as the extent of spare capacity (reserve plant margin). The modelling showed that there was an ambiguous relationship between the level of horizontal integration and BidIndex across different model specifications, so it would be difficult to conclude that horizontal mergers are the reason for higher prices.

³² This reported investigated the determinants of bidding only only; the determinants of wholesale price, were not studied in any detail and are beyond the scope of this report.

- 64 The modelling did however produce a rather striking result when it came to the relationship between reserve plant margin and Bidding Changes. The model shows that decreases in reserve plant margin (i.e. supply shortages) tend to be associated with statistically significant increases in BidIndex.
- 65 The size of this effect is material: the 10 percentage point fall in the margin from 2015 to 2017 is estimated to account for a 5 percentage point increase in high bidding and capacity not being made available. This result would be consistent with the proposition that recent increases in wholesale electricity prices are caused principally by worsening supply shortages. This outcome is expected as more expensive generators run and set the price more frequently as supply shortages become more acute.
- 66 The reason supply shortages are arising is because NEM investors are no longer responding to higher wholesale prices by building new generators like they did in the past. This change in investor behaviour is not due to market power or a malfunctioning NEM design. This change in investor behaviour is due to the extreme uncertainty surrounding carbon pricing. Currently, no generation investment is viable unless it is subsidised, long term, by the government. This is because there is no unsubsidised generation investment that is viable both with and without a carbon price (at least a carbon price sufficient to achieve Australia's Paris commitments) and investors expect that some form of carbon pricing is highly likely to apply at some point over the life of an investment. In the face of such risk, investors are waiting for resolution on carbon pricing and/or waiting for prices to reach a high enough level to justify taking the higher investment risk.

Table 2: Regression results from various model specifications

	BidIndex	BidIndex	BidIndex >0.5	BidIndex	BidIndex	BidIndex >0.5
Method	OLS	OLS	Logit	Fractional Logit	Fixed Effects	Fixed Effects Logit
Capacity (GW)	-0.102	-0.102	-1.23	-0.523	0.108	-0.109
	(-12.38)**	(-12.38)**	(-10.66)**	(-12.39)**	(0.40)	(-0.07)
Time	0.00107		0.00355	0.00666	0.00167	0.0128
	(0.67)		(0.22)	(0.76)	(1.24)	(0.63)
HHI	0.0000897	0.0000809	0.000378	0.000518	0.0000893	0.000718
	(2.07)*	(1.95)	(0.84)	(2.11)*	(1.4)	(1.23)
MarketVI	0.0225	0.113	0.963	0.0988	0.0279	1.59
	(0.15)	(2.17)*	(0.66)	(0.12)	(0.22)	(0.86)
OwnerVI	-0.0381	-0.0378	-0.256	-0.228	-0.0519	-0.642
	(-3.45)**	(-3.42)**	(-2.31)*	(-3.65)**	(-2.02)*	(-3.30)**
ReserveMargin	-0.468	-0.470	-4.22	-2.78	-0.408	-5.66
	(-4.04)**	(-4.07)**	(-3.51)**	(-4.23)**	(-2.24)*	(-3.62)**
N	5,029	5,029	4,741	5,029	5,029	3,506

Source: Frontier Economics analysis. * indicates $p < 0.05$; ** indicates $p < 0.01$.

APPENDIX: REGRESSION ANALYSIS EXPLAINED

67 Frontier Economics has used regression analysis to investigate the factors that may have contributed to Bidding Changes, specifically vertical integration, both of the overall market and individual generators. In order to explain what regression analysis is, and what it does, the following note explains:

- how **regression** can be used to examine the nature of the relationship between variables and measure the strength of the relationship
- how a **dummy variable** can be used to measure the difference in bidding behaviour between different vertically integrated generators and stand-alone generators

68 We also explain how regression relationships are estimated and how to interpret supplementary information calculated during the estimation process to assess the contribution of individual variables.

Regression analysis

69 Regression analysis is a statistical methodology³³ for investigating the relationship between an item of primary interest, such as the price of a product, and other items, such as cost or order size, that might have an influence on the price. The item of interest is referred to as the **dependent** or response variable, and the items that might influence the dependent variable are referred to as the **independent** or explanatory variables, or drivers.

70 The postulated relationship between the dependent variable and the independent variables can be written as an algebraic equation. This specifies precisely how the independent variables are assumed to influence the dependent variable. This equation is referred to as the regression equation or regression model, or similar expressions such as the econometric model or the statistical model.

71 When there is only one independent variable in the regression model it is referred to as ‘simple’ regression; when there are more independent variables the model is referred to as ‘multiple’ regression.

72 At the most basic level, regression analysis is akin to drawing a line of best fit on a scatterplot. That is, obtaining the vertical intercept and slope of a line that best fits the data. But while it provides the slope, the estimated effect of the independent variable on the dependent variable, it also provides information regarding how confident we are in this estimated value. In certain conditions³⁴ we expect that that the estimated effect is quite close to the true effect, whereas in others we must acknowledge that our estimate is not sufficiently informative. The true effect is

³³ When analysing economic or business data, the term ‘econometric’ is often used instead of ‘statistical’. Regression analysis is also referred to as ‘regression modelling’ or ‘econometric modelling’.

³⁴ Many data points, the explanatory variable takes values over a wide range, and the data does not exhibit a substantial degree of randomness.

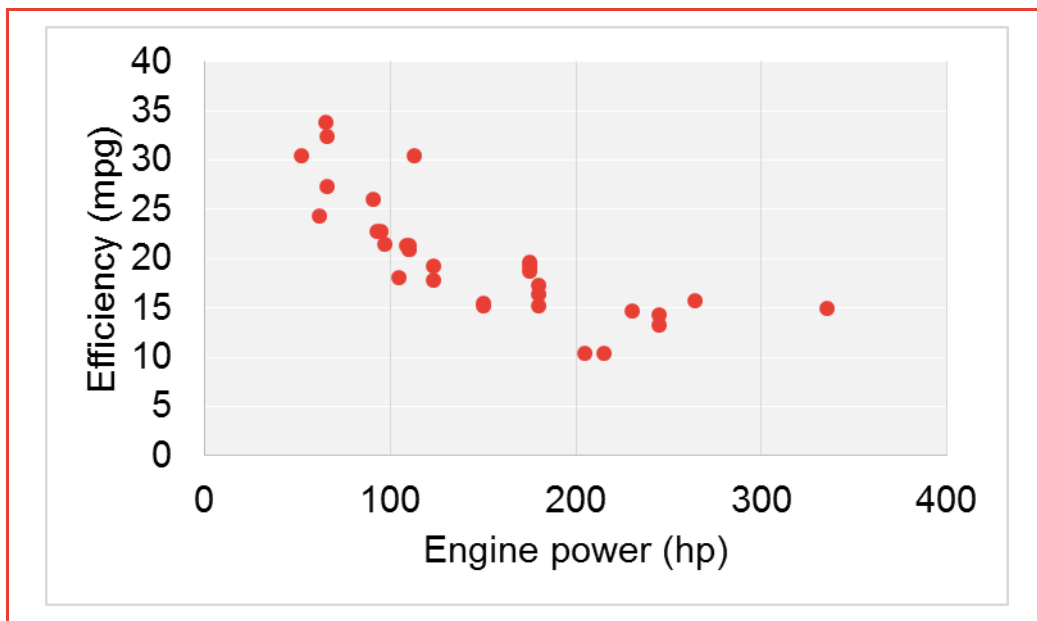
almost always unobserved, we merely estimate it and use the information to make inference about what values are reasonable or plausible with some degree of confidence.

73 To illustrate, suppose we are interested in exploring the relationship between the efficiency of cars (as measured by the miles per gallon) and the engine power of cars (measured by horsepower, hp). A simple means of investigating whether there is a relationship or association between these two variables is to produce a scatterplot of the two variables – with the dependent variable, mpg, plotted on the vertical (or y) axis and the independent variable, hp, plotted on the horizontal (or x) axis. This scatterplot is shown in Figure 5.³⁵

74 This scatterplot shows that efficiency decreases with engine power. The bigger the engine, the more fuel required. This indicates that there is a **negative** association between the two variables. We say that the association is negative because as one variable increases (changes in a positive direction) the other tends to decrease (changes in a negative direction).

75 A possible regression model for the relationship between *mpg* (the dependent variable) and *hp* (the independent variable) is a straight line through the points on the graph.

Figure 5: Plot of engine power vs efficiency



Regression model

76 The algebraic equation for a straight line regression model is the simple textbook straight line equation:

$$y = a + b * x \tag{1}$$

³⁵ Data used for illustrative purposes, taken from Motor Trend car road tests database.

77 where a is the intercept that the line makes on the vertical or Y-axis, b is the slope of the line and the symbol $*$ denotes multiplication. The slope is an indication of how much a change in the value of the x variable (order quantity, in this example) affects the value of the y variable (price). A large value of b corresponds to a steep slope and a strong influence of x on y , while a small value of b corresponds to a flat slope and a weak influence of x on y . Of course, the units in which x and y are measured have to be taken into account when making this statement.

78 The intercept and slope are also referred to as parameters or coefficients.³⁶ In terms of the variables in our example we can write the postulated regression model as:³⁷

$$mpg = a + b * hp \quad (2)$$

Estimation

79 Estimation of a regression model is the process of determining the intercept and slope of the line that provides the best fit (in some sense) to the points on the graph. A common way to do this is to find the line that minimises the overall distance between the points and the line (the line is commonly referred to as the 'fitted' line). The distance between each point and the fitted line is measured in a vertical direction, i.e. the distance that the price is above or below the line.

80 These distances are then squared and added together.³⁸ The line that makes this sum as small as possible is known as the least squares (LS) regression line.³⁹ Under fairly broad technical assumptions, the LS regression line is 'best' in a specific statistical sense.

81 In the present example the least squares regression line has the following equation:

$$mpg = 30.099 - 0.0682 * hp \quad (3)$$

82 Thus the estimated parameters are 30.1 for the intercept and -0.068 for the slope coefficient. The slope coefficient indicates that an increase in the engine power of 1 horsepower leads to a decrease in the efficiency of 0.068 miles per gallon. Figure 6 shows how this 'estimated' or 'fitted' line fits through the original data.

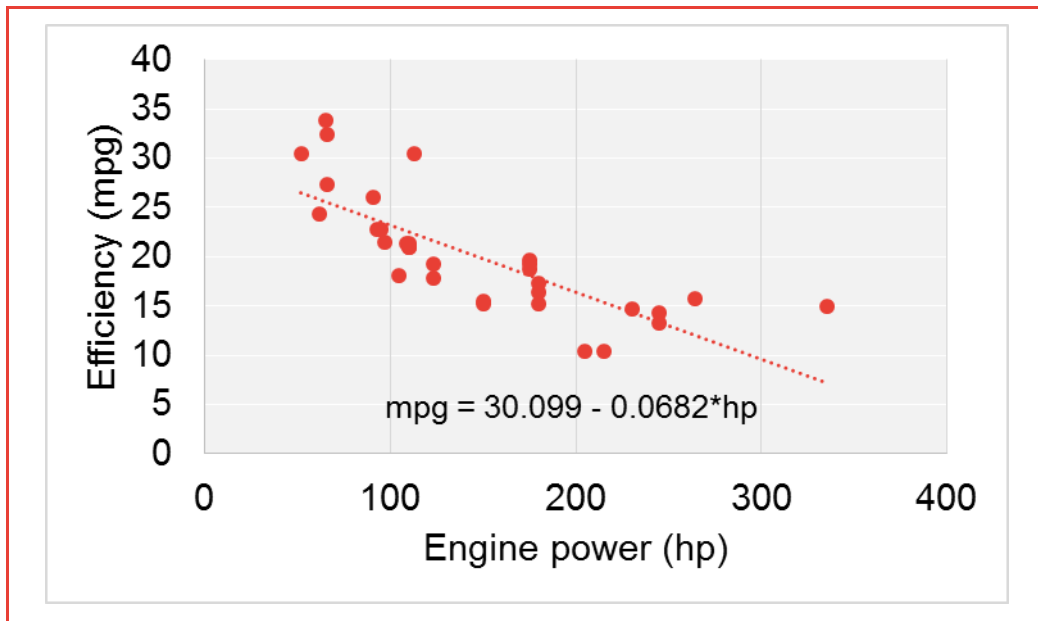
³⁶ Coefficients that are multiplied by an independent variable in the equation are sometimes referred to as slope coefficients to distinguish them from the intercept.

³⁷ For brevity the error term is omitted from the equation displayed. This term captures the effect of randomness and variables not explicitly controlled for.

³⁸ The distances are squared to avoid positive and negative distances cancelling each other out.

³⁹ The approach is also known as 'ordinary least squares (OLS)' or 'OLS regression'.

Figure 6: Least squares regression line for how engine power affects efficiency

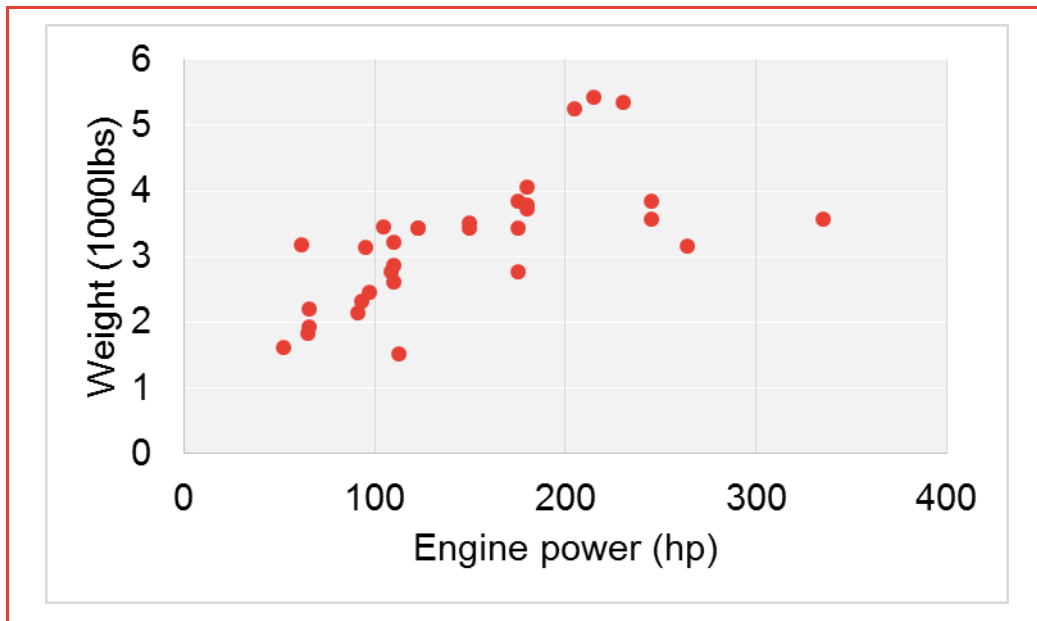


83 We note that the data points do not lie exactly on the line. This indicates that there is a reasonable degree of uncertainty in the true effect. While our estimated effect is -0.068 , the true effect may be substantially different from this estimate. The extent to which our estimates lack precision can be evaluated.

Multiple regression

84 In the above we observed a negative relationship between engine power and efficiency. Yet in doing this we ignored the effect of all other variables. In particular, vehicle weight is plausibly related to efficiency. Moreover, weight may be related to engine power, as shown below.

Figure 7: Plot of engine power vs weight



85 Thus, the conclusion regarding the effect of engine power is premature and ultimately unreliable. We cannot, *ex ante*, be sure if the effect is genuine or instead merely reflective of the positive association between engine power and vehicle weight. Accordingly, we must account for both variables.

86 When there is more than one independent variable in the regression model it is referred to as multiple regression. While it is harder to illustrate on a graph how multiple regression works, algebraically it involves only a small addition to the simple regression model; for each additional independent variable we add that variable multiplied by a coefficient to the equation. For example, if we want to investigate the way both power and weight influence efficiency we can postulate the relationship:

$$mpg = a + b * hp + c * weight \quad (4)$$

87 Estimation of this multiple regression model follows along the same lines as for the simple regression model. However, a new issue arises if some of the independent variables are closely correlated with each other. In that case, the slope coefficient associated with one particular independent variable may, in fact, be picking up the impact on the dependent variable of another, correlated, independent variable. For example, if the engine power is closely related to the vehicle weight, then for heavy cars the engine power will always be high, and for light cars the engine power will be low. That might make it difficult to separate the roles that weight and power play in determining efficiency. This is known as the multicollinearity problem.

88 Multicollinearity occurs when two or more independent variables are closely correlated. This does not affect how well an equation fits the data, but individual coefficient estimates may change in an unexpected way when small changes are made to the model or to the data. Thus while the overall model might fit the data well, predictions of the impact of changes in individual independent variables may not be reliable. The degree of precision can, however, be obtained.

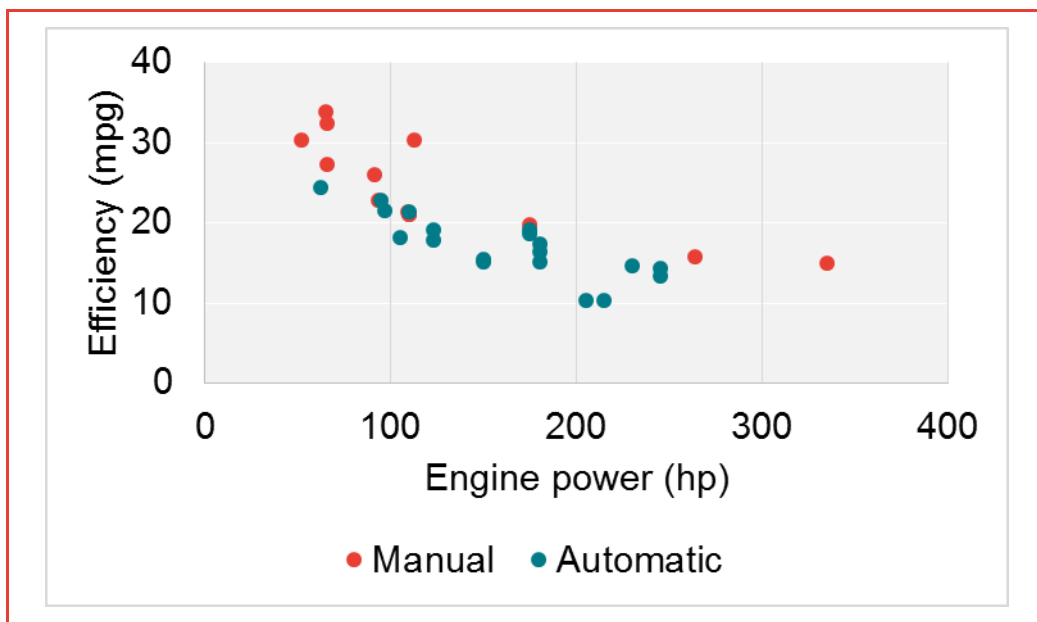
89 Regardless, in this case we are able to estimate the equation and obtain the following relationship,
noting the change in the estimated effect of engine power:

$$90 \quad mpg = 37.23 - 0.032 * hp - 3.88 * weight \quad (5)$$

Dummy variables

91 Dummy variables are used in regression models to estimate the impact on the dependent variable
of observations falling into one or other of two categories. Suppose, for example, we wish to
account for whether the transmission were automatic or manual. It would be important to account
for this impact using regression analysis instead of simply comparing the average efficiencies of
manual and automatic cars. Similar to above, other variables are relevant and may be related to
transmission type.

Figure 8: Engine power vs efficiency, by transmission type.



92 To investigate this question statistically, we can define a variable, say *manual*, which takes the
value 1 if the car has a manual transmission, and 0 otherwise. Examining Figure 8 above, it appears
plausible that cars with a manual transmission would have a higher efficiency than those with an
automatic transmission. Of course we would need to also account for vehicle weight. This is
difficult to visualize, yet can be easily performed by extending equation (5) to include the dummy
variable:

$$93 \quad mpg = a + b * hp + c * weight + d * manual \quad (6)$$

The coefficient of *manual* i.e. *d*, indicates the amount by which manual cars are more efficient
than automatic cars. The estimated least squares line for this model is:

$$94 \quad mpg = 34.00 - 0.037 * hp - 2.88 * weight + 2.08 * manual \quad (7)$$

This indicates that, all else equal, a manual car has an efficiency 2.08mpg higher than an automatic.

Assessing the estimated model and coefficients

95 In addition to providing the estimates of the coefficients in the regression equation, the statistical and econometric software packages used for regression analysis produce a range of supplementary information useful to the analyst in assessing the estimated regression model. To explain how this information assists the analyst to assess the estimated regression model we will use the example models discussed in the previous subsection.

96 In Figure 9 we reproduce the regression output provided by the Stata software package for the estimated regression equation (5) discussed in section 0. In the figure we have highlighted a block of information that is of particular interest to an analyst.

Figure 9: Regression output for estimated equation (6)

```
. reg mpg hp weight manual, vce(robust)
```

Linear regression		Number of obs	=	32
		F(3, 28)	=	36.56
		Prob > F	=	0.0000
		R-squared	=	0.8399
		Root MSE	=	2.5375

mpg	Robust				[95% Conf. Interval]	
	Coef.	Std. Err.	t	P> t		
hp	-.0374787	.00787	-4.76	0.000	-.0535996	-.0213579
weight	-2.878575	.8917752	-3.23	0.003	-4.705294	-1.051857
manual	2.08371	1.347888	1.55	0.133	-.6773131	4.844733
_cons	34.00288	2.59665	13.09	0.000	28.68388	39.32187

Assessing individual coefficients

97 We refer to the output in the highlighted block above to explain the information provided by the regression estimation procedure that is relevant to assessing individual coefficients.

98 The first column in the block provides the names of all the variables in the model; mpg is the dependent variable, and the independent variables are hp (engine power), weight, the dummy variable for manual transmission and the intercept or constant term.

99 The second column, headed 'Coef.' provides the least squares estimates of the **coefficients** in the model. These have been reproduced in equation (7).

100 The **t-value** and **p-value** for each coefficient provide information for testing a specific hypothesis about that coefficient, namely that the coefficient is not different from 0. If this hypothesis is true, then the associated variable does not assist in explaining the dependent variable.

101 The t-value for any coefficient needs to be interpreted together with the associated p-value. The p-value tells us the probability that, if the null hypothesis were true, we could have obtained a t-value as large or larger (in absolute value). In other words, it gives the probability that the t-value could

have been obtained by pure chance. The smaller the p-value, the more confidently we can reject the null hypothesis.

102 In order to determine whether a coefficient is different from 0, it is common to first decide on a level of significance. Commonly used levels of significance are 5% and 1%. If the p-value for a coefficient is smaller than the chosen level of significance we say that the coefficient is significantly different from 0, or simply 'significant', at the chosen level of significance. To be significant at a particular level of significance, say 5%, means that the probability of obtaining an estimated coefficient as large as this (in absolute value) by chance is less than 5%.

103 Note that a coefficient can be significantly different from 0 at one level of significance (say 5%), but not at a lower level of significance (say 1%). In our example the p-values for the power and weight coefficients are smaller than any commonly used level of significance.⁴⁰ Thus we can conclude that power and weight have a statistically significant effect on efficiency. However, we cannot make the same claim for the effect of transmission type: the p value is too large for us to justify making a conclusion regarding the effect, the degree of uncertainty is too high.

⁴⁰ The correlation between weight and power was sufficiently weak that we were able to reliably tease out the impacts of the two variables. The correlation coefficient between the two variables was 0.659.

