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The Influence of Administrative Intensity on Efficiency: An Empirical Analysis of Australian Universities

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While a voluminous empirical literature has investigated university efficiency, much less attention has focused on the impact of administrative intensity on university performance. In this article, we seek to contribute to the empirical literature by examining the relationship between operational efficiency and administrative intensity in the Australian higher education sector over the period 2009/10–2018/19 using a second stage bootstrapping Data Envelopment Analysis (DEA) fractional regression model. We find that administrative intensity positively affects the performance of universities for both the standard and bias-corrected efficiency models. Moreover, administrative intensity exhibits an inverted U-shaped relationship with university efficiency. We also find that administrative intensity has a differential impact on the efficiency of the different types of university. Various public policy implications are considered.

Keywords: administrative intensity, Australian universities, operational efficiency.

1. Introduction

In higher education systems worldwide, universities face difficult ongoing challenges, many of which have intensified due to the COVID-19 pandemic crisis (Burki, 2020). In common with other public organisations characterised by high fixed costs, universities have often reacted to financial pressures with reductions in staff in tandem with other cost saving measures (Howard, 2021). In the empirical literature on the public sector, it has been established that public organisations typically display allocative inefficiency due to excessive expenditure on administrative functions (Kelman, 2006; Pandey, 2010). Furthermore, administrative bureaucracies within these public entities frequently expand even though aggregate organisational size declines (Parkinson, 1957; Boyne, 1986; Boyne & Meier, 2013). In the public administration literature, numerous scholars have argued that public sector entities with a lower-level administrative intensity (i.e. a smaller proportion of administrators relative to other staff) can operate more efficiently (Ford & Slocum Jr, 1977). From a public policy perspective, it is thus important to determine the impact of administrative intensity on the various

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dimensions of organisational performance, including in higher education systems, such as the Australian public university system.

While some empirical effort has been directed at administrative intensity in the Australian university system, especially on the question of administrative scale economies (Tran & Dollery, 2022), much remains to be done. In particular, to date there has been no empirical examination of the impact of administrative intensity on the operational efficiency of the Australian university system. Operational efficiency measures the relationship between inputs, such as academic staff, administrative staff and buildings, and outputs, like research output and student numbers. An entity is operationally efficient when it maximises its output from its inputs (Fried *et al.*, 2008). This article thus addresses this gap in the empirical literature.

We investigate the relationship between administrative intensity and operational efficiency in the Australian higher education sector over the period 2009/10–2018/19 using a second stage bootstrapping Data Envelopment Analysis (DEA) fractional regression model. Two specific research questions are addressed: (a) What is the relationship between administrative intensity and operational efficiency in Australian universities and (b) is there a difference between the different categories of university with respect to the relationship between administrative intensity and university efficiency. These questions can offer valuable insights to university managers and public policy makers alike.

The article is divided into five main parts. Section 2 provides a synopsis of the empirical literature and develops the two research hypotheses. By way of institutional background, Section 3 briefly describes the main features of the Australian public university system. Section 4 outlines the research strategy adopted in the article, whereas Section 5 presents the empirical results of the modelling exercises. The empirical results are considered in detail in Section 6. The article ends in Section 7 with some brief concluding remarks.

2. Analytical Perspectives and Research Hypotheses

This section focuses on hypothesis development through a synoptic review of the literature on university efficiency in Australia and other countries and the impact of administrative intensity on university performance proxied by different indicators. This approach is adopted to investigate the relationship between efficiency and administrative intensity in the Australian university context and determine whether this relationship differs between the various university groupings, as noted in our research objectives.

Many previous studies have examined the efficiency of Australian universities. Early studies, such as Abbott and Doucouliagos (2003), Carrington *et al.* (2005) and Coelli (1996), focused on numerous inputs and outputs and employed DEA to estimate the levels of efficiency in Australian universities. For example, Abbott and Doucouliagos (2003) investigated technical and scale efficiency using 1995 data and found that Australian universities exhibited high levels of efficiency. Similarly, Carrington *et al.* (2005) estimated that the average scale efficiency of Australian universities for the period 1996–2000 was 92 per cent, implying that there was scope for improving efficiency. Moreover, Carrington *et al.* (2005) also found non-metropolitan location had a positive effect on efficiency while the proportion of students from rural and remote regions had a significant negative impact.

Worthington and Lee (2008) investigated the trends in productivity in Australian universities over the period 1998–2003 employing Malmquist indices. They found that productivity grew by 3.3% in Australian universities largely due to technological progress, further observing that smaller and more recently established universities accounted for larger gains in productivity compared with larger and older universities. Abbott and Doucouliagos (2009) examined the role of competition for international students on the efficiency of Australian universities (from 1995 to 2002) and New Zealand universities (from 1997 to 2003). They found that competition for international students had led to improved efficiency in Australian universities, whereas it had no impact on the efficiency of New Zealand universities. Lee and Worthington (2016) found that the standard DEA models that assume constant returns to scale overestimated the efficiency scores of Australian universities. A more recent study by Duan (2019) found that Australian universities operated at higher levels of efficiency over the period 2011–2015.

As we have seen, operational efficiency in a university system refers to the relationship between inputs and outputs, where higher levels of output per unit of input denote higher levels of operational efficiency. At an intuitive level, in the Australian university sector outputs have customarily been construed in terms of students enrolled and/or graduating as well as research grants and research publications. Given the absence of adequate measures of the quality of education provided, efficiency scores might be biased in favour of high output low-quality student graduation outcomes (Abbott & Doucouliagos, 2003). By contrast, inputs consist of academic staff and administrative staff, together with buildings and facilities. In the present context, administrative services consist of a subset of specific administration processes underpinning teaching, like secretarial services and student services, as well as administrative processes supporting research activities, such as research grant officers and library services.

The efficiency and productivity of higher education institutions has been extensively investigated outside of the Australian context. For example, Agasisti and Berbegal-Mirabent (2021) completed a cross-country study of universities in eight European countries for the period 2011–2013 and estimated the average efficiency score at 0.571, thereby implying there was significant scope for productivity gains. Similarly, Andersson and Sund (2022) investigated technical efficiency and productivity in universities in Nordic countries for the period 2011–2016. They found that the average inefficiency score was 10.1%. Staff turnover was identified as being positively correlated with inefficiency scores. Other studies considered the efficiency of higher education institutions in England (Papadimitriou & Johnes, 2019), Southern European countries (Martínez-Campillo & Fernández-Santos, 2020), Slovakia (Kubak *et al.*, 2019), Colombia and Spain (Ramírez-Gutiérrez *et al.*, 2020), Turkey (Mammadov & Aypay, 2020), South Africa (Myeki & Temoso, 2019), Vietnam (Tran & Villano, 2017) and India (Johnes *et al.*, 2020).

However, to date there has been limited effort focused on the impact of administrative intensity on the operational efficiency of universities. Some empirical work has been undertaken. For example, Andrews *et al.* (2017) investigated the effect of administrative intensity on British university research, grant and PhD performance for the period 2005–2011. Their findings revealed that these relationships were inverted U-shaped. They argued that large complex public organisations can benefit from allocating additional resources to administration as proposed by structural contingency theory. Romine *et al.* (2018) examined the relationship between administrative intensity and student retention and success, and they found that aggregate faculty salary expenditure was positively related to student retention and that the proportion of full-time faculty members was also positively related to student retention. This suggests that the proportion of adjunct staff (equivalent to casual employees) is negatively correlated with student retention. In a recent study by Ryu and Christensen (2019), who examined the influence of administrative intensity on student achievement in Texas school districts, they found that this association was inverted U-shaped. Most recently, Taggart (2021) investigated the impact of administrative intensity on faculty job stress and found that increased administrative responsibilities placed on academic staff due to reduced clerical and secretarial support resulted in heightened stress. The increased administrative burden on faculty members in some instances led to additional stress for faculty undertaking research, teaching or service. In other instances, increased administrative work had a negative impact on the work-life balance of faculty members. While these extant studies provide some insights into the impact of administrative intensity, they do not capture the aggregate effects of administrative intensity on the efficiency of higher education institutions.

Given this gap in the empirical literature, in this article we empirically investigate the impact of administrative intensity on the operational efficiency of Australian universities. Following related empirical studies in public sector management, we apply structural contingency theory to the relationship between administrative intensity and efficiency in the Australian university system. Structural contingency theory contends that public sector organisations that allocate more resources to administrative support functions can more effectively coordinate and synchronise organisational processes and thereby improve their efficiency (see for instance, Tran and Dollery (2022), Van Helden and Huijben (2014) and Walker (2014)). We thus hypothesise that the efficiency of higher educational institutions is positively related to the administrative intensity of these entities.

Hypothesis 1: *There is a positive relationship between administrative intensity and operational efficiency in Australian universities.*

However, the relationship between administrative intensity and operational efficiency may not be monotonic. When the aggregate demand for academic services rises in proportion to student size, a decrease in administrative support may be necessary to maintain the operational efficiency of universities. This is particularly the case in recent times with the impact of the COVID-19 pandemic on Australian universities. It is thus plausible that the relationship between administrative intensity and operational efficiency may be non-linear.

It is also likely that the effects of administrative intensity on operational efficiency may vary among different universities or groups of universities. Prior studies have found important differences among groups of Australian universities. These studies often identify three distinct groups of universities – 'Dawkins universities', 'non-Dawkins universities' and the 'Group of Eight' universities – where Dawkins universities are those that were established subsequent to the 1988 Dawkins White Paper. Duan (2019) adopts a classification of four categories of Australian university based on their size and differential focus on research versus teaching. These four groups consist of the Group of Eight (G08) universities, the Australian Technology Network (ATN) universities, the Innovative Research Universities (IRU) and the New Generation Universities. However, Heffernan (2017) adopts five types of university including the Go8, IRU, ATN, Regional University Network (RUN) and non-Aligned Universities (NAU). These university groups exhibit differences in their development strategies. For instance, the Go8 is focussed on developing elite international alliances and research partnerships (G08, 2022) while the ATN brings together five universities with a focus on enterprise and finding solutions to problems facing the Australian economy and society (ATN, 2022). On the other hand, the RUN shares a commitment to transforming their regions through education and research to contribute to regional economic and social development (UNE, 2022). The IRU is committed to inclusive excellence in teaching and research (IRU, 2022). Universities in the NAU group have their own differential commitments to teaching and research objectives. These university groupings typically present their distinctive characteristics as comparative advantages in the Australian higher education sector.

In contrast to structural contingency theory, public choice theory has sharply opposing implications on the relationship between administrative intensity and operational efficiency (Andrews & Boyne, 2014; Rutherford, 2016). For example, Andrews and Boyne (2014) argue that task complexity and organisational size have significant implications for the relationship between administrative intensity and organisational operational performance. Rutherford (2016) argues that excessively low levels of administrative intensity may lead to the inadequate coordination of various administrative tasks leading to a negative impact on operational efficiency. Increased administrative intensity under these circumstances can thus lead to the improved coordination of complex tasks and thereby greater operational efficiency. However, beyond an optimal level of administrative intensity, additional resource outlays on administration intensity may have an opportunity cost in terms of fewer academic staff and accordingly lead to sub-optimal outcomes. Nevertheless, given the differences between the nominated groups of Australian universities, the extent of administrative intensity may have varying effects on the operational efficiency of these groups of universities. This leads us to our second hypothesis.

Hypothesis 2: *There is a difference between the different categories of university with respect to the relationship between administrative intensity and university efficiency.*

3. The Australian Higher Education Sector

The Dawkins reform program in the late 1980s forced far-reaching structural change on the Australian higher education system. The Dawkins reform program had a plethora of objectives, including improving the productivity and operational efficiency of the university sector. The program had sweeping consequences for the Australian university sector, including the introduction of mass university education, radical changes in university financing arrangements and enabling Australian universities to become major providers of education to international students (Worthington & Higgs, 2011). As a result, enrolments at Australian universities grew by 37% over the period 2008–2017, with the number of international students increasing by 220% between 2002 and 2017.

Figure 1 illustrates the growth in student numbers in 37 public universities (Department of Education (DOE), 2022) in terms of undergraduates, postgraduate and other degrees, classified by university groups. As can be seen, the average undergraduate enrolments of Australian public universities has steadily increased from 19,336 in 2009/2010 to 25,089 in 2018/2019. Similarly, postgraduate student numbers have grown at a lower level during this period, reaching approximately 11,000 students in 2018/19. However, student numbers in other degree programs remain largely unchanged. As we can see in Figure 1, the Australian Technology Network demonstrated the highest student growth rate in bachelor degree numbers, followed by the Group of Eight. The Regional University Network was leading in in the other degree category, although it ranked last in bachelor degree numbers. The Group of Eight universities ranked top in postgraduates, followed by the Australian Technology Network universities while other groups showed a stable level in postgraduate numbers. In general, all groups demonstrated growth in student numbers at different levels.

Structural contingency theory holds that an increase in student numbers should lead to a rise in the proportion of administrative staff to respond to increased demand for learning and teaching services and thereby improve overall organisational performance (Walker, 2013; Van Helden & Huijben, 2014). Conversely, public choice theory holds that administrative intensity increases in line

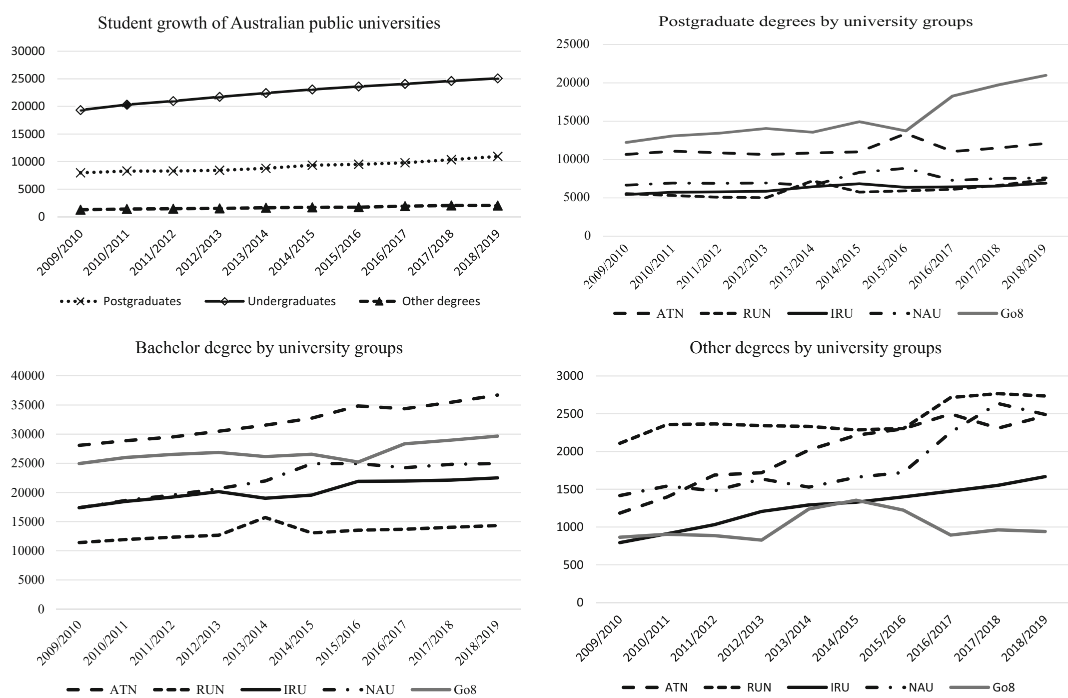

Figure 1. *Student growth over years, classified by university groups, 2009/2010–2018/19. Source: DOE (2022), own elaboration*

Table 1. *Total students and annual expenditures of Australian public universities by year and by university groups (n = 37)*

Year	Total students	Total expenses ($'000)	Academic related expenses	Administrative related expenses	Other expenses
2009/2010	146,164	500,929	153,288	135,879	211,762
2010/2011	153,189	540,427	166,750	147,230	226,446
2011/2012	156,665	582,780	180,215	158,724	243,842
2012/2013	161,134	624,566	194,312	171,155	259,100
2013/2014	167,550	651,628	200,015	178,934	272,679
2014/2015	172,569	693,719	211,061	190,413	292,245
2015/2016	177,704	723,182	217,411	196,498	309,273
2016/2017	181,630	766,710	229,594	207,331	329,786
2017/2018	187,621	805,998	241,171	218,322	346,504
2018/2019	193,483	866,424	254,265	231,001	381,157
Average students and expenses by university groups, 2009/10–2018/19					
RUN	7238	294,892	83,675	84,688	126,530
IRU	9241	486,496	148,926	137,837	199,733
NAU	10,476	514,343	159,064	142,380	212,898
ATN	15,190	755,822	240,252	211,584	303,987
Go8	14,445	1,325,786	394,724	343,989	587,073

Source: DOE (2022), own elaboration. RUN: Regional University Network, IRU: Innovative Research University; NAU: Non-aligned Universities; ATN: Australian Technology Network and G08: Group of Eight.

with public budgetary expansion, as well as with organisational size, thereby generating greater wasteful levels of bureaucracy (Boyne & Meier, 2013). This could potentially diminish the operational efficiency of organisations (Peters, 2001; Boon & Verhoest, 2014).

In economic terms, the student/academic ratio averaged 14.4 and the proportion of international students in total student enrolments averaged 26% over the period 2009/10–2018/19 (DOE, 2022). Howard (2021) has demonstrated that the proportion of staff costs relative to operating income represents a crucial performance benchmark in the university system, where non-academic staffing costs rose by $3.99 billion between 2003 and 2019 period and $1.13 billion in the 2014–2019 period. In aggregate, the ratio of academic staff costs to university income has fallen over time, whereas the proportion of non-academic staff costs has remained constant. This serves to underline the critical importance of determining whether Australian universities have been efficient given that administrative outlays have grown in line with university size by student numbers.

Total student numbers and annual expenditures of Australian public universities by year and by university group are shown in Table 1. Total university expenditure increased by an average of 6.3%, more than twice the average student growth rate at 3.2% over the reported period. University administrative costs (i.e. non-academic expenses) rose by 6.1%, whereas academic costs increased by 5.8% on average. Administrative expenditure refers to administrative outlays including salaries, contributions to superannuation schemes, payroll taxation, workers compensation, long service leave expenses, non-annual leave, and other employee benefits (DOE, 2022). An increase in total expenditure may seek to meet higher demand for learning and teaching activities. However, whether this increase in outlays is efficiently utilised, especially in non-academic activities, should be investigated.

Table 1 shows different levels of average expenditure classified by university groups. The Go8 group was ranked top in average total expenditure, followed by the ATN, NAU, and IRU. The RUN group was ranked bottom in its average expenditure. However, its student numbers were the lowest. It can be observed that the higher student numbers, the greater total expenditure. However, the ATN had higher student numbers than the Go8, while its average expenditure was lower than that of the Go8. As shown in Figure 1, the ATN had an increasing in student numbers in degrees that might cost less than postgraduate degrees or bachelor degrees in terms of teaching and learning activities.

A substantial empirical effort has been directed at investigating the performance of Australian universities, including Avkiran (2001), Abbott and Doucouliagos (2003), Abbott and Doucouliagos (2004), Carrington *et al*. (2005), Madden *et al*. (1997), Lee and Worthington (2016), Worthington and Higgs (2011) and Zhang and Worthington (2017). In general, these studies have found that Australian universities have performed at relatively high levels of efficiency, including around 0.9 on average for cost and operational performance. However, at 0.9 there is still room for a roughly 10 per cent improvement to achieve full technical efficiency. These findings are broadly in line with the performance of British universities Flegg *et al*. (2004). By contrast, Carrington *et al*. (2018) established that productivity in the Australian university sector increased by 1.1% per annum over the period 2005–2010, with 1% owing to technical efficiency increases and 0.1% due to technical innovation. Moreover, they found that the value of operational grants to universities could be lowered by 1.76% per annum, roughly equivalent to around $100 million. This indicates that universities have not used public funding efficiently.

Although a substantial empirical literature has investigated cost efficiency, operational efficiency and productivity in Australian public universities, little research has been directed at administrative intensity in the university sector, with the exception of the Tran and Dollery (2022) study on economies of scale in administrative intensity at Australian universities. While Tran and Dollery (2022) investigated the influence of university size by students, staff size and task intensity on administrative intensity as the dependent variable, our article aims to examine further whether administrative intensity as an explanatory variable can explain variation in the operational efficiency of universities. The findings of our article are expected to generate information to assist educational managers and policymakers in designing more appropriate strategies to improve university performance through modifying the degree of administrative intensity in their organisations.

4. Empirical Strategy

In order to address the two research hypotheses, we first estimate the operational efficiency of Australian universities and then investigate the impact of administrative efficiency on the operational performance of universities for the whole sample in the presence of control variables over the period 2009/10 to 2018/19. In addition, we stratified the sample into five discrete categories – Go8, ATN, IRU, RUN and NAU – following Heffernan (2017) and then examined the sector as a whole sector as well as each university group.

Accordingly, our empirical strategy consists of two main steps.

4.1. Step 1: Estimating the efficiency of Australian Universities

In the empirical literature on efficiency estimation, two conventional approaches have been used to investigate the efficiency of decision-making units: DEA and Stochastic Frontier Analysis (SFA). The DEA approach has attracted more interest from researchers because multiple inputs and multiple outputs can be employed in this model without price information. Furthermore, no pre-specification of the functional form is required under the DEA approach, whereas this is essential under the SFA approach (Coelli *et al*., 2005; Jacobs, 2001; Tran & Villano, 2018). DEA has been applied across numerous sectors and is widely accepted as a means of estimating university efficiency (Carrington *et al*., 2005; Duan, 2019; Bowrey & Clements, 2020).

In this article, we seek to estimate the efficiency scores for individual universities using the standard DEA approach for the period 2009/10 to 2018/19; a method initially developed by Charnes *et al*. (1978) and based on the assumption that production technology exhibits constant returns to scale (CRS). Because in practice not all production units operate at the optimal scale – often because of scale effects or external factors – Banker *et al*. (1984) extended their model to incorporate variable returns to scale (VRS) to capture scale effects. Accordingly, under a DEA VRS specification, pure technical efficiency can be estimated independent of scale effects. Our use of the DEA VRS approach allows us to estimate the efficiency scores of Australian universities. Details of the linear programming of this method are presented in Appendix A1. The estimated efficiency scores from the standard DEA approach could contain potential biases because sampling variation and random errors are not accounted for (Simar & Wilson, 2000). Thus, the bootstrap technique introduced by Simar and Wilson (1998) was employed to circumvent this problem. Bootstrapping enables the assignment of measures of accuracy to sample estimates, such as bias, variance and confidence intervals. Details of the bootstrapping procedure are discussed in Simar and Wilson (1998) and many software packages (such as DEAP, rDEA and MaxDEA) are available to generate bootstrapped efficiency scores. We employed this method to obtain more robust efficiency estimates.

To secure empirical evidence on the choice of VRS, a returns-to-scale (RTS) test was undertaken to investigate the null hypothesis: H_0: RTS is constant versus the alternative hypothesis H_1 that RTS is variable. We ran this RTS test using rDEA package in R (Besstremyannaya *et al.*, 2020) based on the theoretical rationale of the non-parametric RTS test proposed by Simar and Wilson (2002) and Besstremyannaya and Simm (2015), among others. The estimated result yielded a p-value $= 0.01 < \alpha = 0.05$. We thus rejected H_0 that RTS is constant and instead accepted H_1 that RTS is variable in our DEA model.

In terms of input–output orientation, we employed an output-orientated approach to estimate the frontier efficiency of Australian universities by using existing inputs to maximise the outputs. Given that Australian universities receive government funding for the provision of education services to students representing the central aim of universities to generate more social benefits, it is optimal to use available input resources to maximise outputs in terms of given education quality. This approach was employed by previous studies (see, for instance, Lee and Worthington (2016) and Duan (2019) in the context of Australian higher education).

The present study seeks to carefully quantify university outputs and inputs although there is no consensus on the most appropriate set of inputs and outputs for estimating the efficiency of a university system (DeWitte and Lopez-Torres, 2017). The choice of inputs and outputs depends on the specific institutional context of the given higher education system under investigation. For example, Carrington *et al.* (2018) used student numbers as the teaching output and books, journal articles, patents, art, software, new medical treatments and other factors as research outputs. They used labour (academic and non-academic) and non-labour costs (depreciation and the return on capital) as inputs to estimate the efficiency and productivity growth of Australian universities. However, Duan and Deng (2016) employed graduate numbers and revenue as outputs while inputs included total staff and total expenditure to estimate the overall performance of Australian universities.

In this article, we use three key inputs – academic staff, non-academic staff and aggregate expenses for university operations – that have been widely employed in the empirical literature. We employ academic and non-academic staff as inputs to gauge the effectiveness of deploying human resources in higher education. In addition, these variables are measured in the number of persons and thus would not overlap with administrative costs that are linked to the estimates of administrative intensity used in Stage 2. Furthermore, aggregate expenditure excluded academic and non-academic staff costs to avoid overstating the efficiency of universities.

With regard to outputs, we use a total of seven outputs comprising three outputs for enrolments of postgraduates, undergraduates and other awards (associate degrees, diplomas, etc.) and four outputs for various types of research income (category 1, category 2, category 3 and category 4). The student outputs have been chosen in line with the academic responsibilities of Australian universities in learning and teaching as shown in the empirical literature of Australian higher education (Stevens, 2005; Flegg & Allen, 2007; Worthington & Lee, 2008; Agasisti & Johnes, 2009; Johnes & Johnes, 2009). However, with respect to research output, there is no general agreement in the literature on estimates for research output (Abbott & Doucouliagos, 2003; Carrington *et al.*, 2005). Some studies have selected the number of journal publications to control for research outputs (Johnes & Taylor, 1991; Madden *et al.*, 1997). However, the quality of research outputs (such as the quality of different journals) is an inherent problem requiring subjective judgement (Carrington *et al.*, 2005). Accordingly, many studies (Johnes & Johnes, 1993; Athanassopoulos & Shale, 1997; Abbott &

Doucouliagos, 2004, 2009) assess research quantity and quality by using weighted indexes of research publications. However, the overlap in number of publications of affiliates who might be adjunct research fellows for several universities can yield double counting. By contrast, research funding (i.e. research income) has been suggested as an appropriate proxy for research output in recent studies (Robst, 2001; Abbott & Doucouliagos, 2003; Carrington *et al.*, 2005). Given the absence of agreed estimates for research output, we used research income as a proxy for research output. Research income demonstrates the capacity and reputation of university in attracting research funding from government and industry. In addition, "the dollar value of research income may reflect the market value of university research output" that is consistent with the government policy (Worthington & Lee, 2008, p. 289). Research income is classified into four categories: Australian competitive grant R&D (Category 1), Other public sector R&D (Category 2), Industry and other R&D (Category 3), and Cooperative Research Centre (CRC) R&D (Category 4). It is argued that research income could be an input. However, according to Abbott and Doucouliagos (2003), much research income/expenditure in Australian universities is allocated on the basis of the research output of universities. There is thus a high degree of correlation between expenditure of research income and research output.

4.2. Step 2: Examining the impact of administrative intensity on University efficiency

Step 2 empirically assesses the two hypotheses that have been discussed above. In order to test H1, we investigate the influence of administrative efficiency on efficiency scores obtained from Step 1 in the presence of control variables. This putative association has not been previously empirically investigated and it thus represents a new avenue of empirical inquiry in the higher education literature.

For H2, we seek to investigate whether the relationship between administrative intensity and efficiency differs between various types of university. Accordingly, as noted earlier we stratified our sample into five groups comprising Go8, ATN, IRU, RUN and NAU to examine if there is any difference in terms of the impact of administrative intensity on efficiency in the presence of the contextual factors.

With respect to the regression model used in Step 2, there is no consensus in the empirical literature on the appropriate regression model to examine the impact of explanatory variables on efficiency. Among the proposed regression models such as the ordinary least squares (OLS) model, Tobit, and fractional regression model (see for example Hoff, 2007; Simar & Wilson, 2007; McDonald, 2009), the fractional regression model (Ramalho *et al.*, 2010; Ramalho *et al.*, 2011) is often preferred due to its usefulness and applicability for two main reasons: (a) the impact of explanatory factors can be examined with respect to the inefficient distance from the frontier if the proportion of the frontier values (equal to one) is sufficiently large and (b) the regression analysis with robust estimates provides valid inferences using their framework. In addition to these advantages, the fractional regression model is adopted for three further reasons: (a) the Farrell (1957) efficiency scores bounded by zero and one can be tested directly on explanatory variables without converting to the Shephard (1970) distance efficiency scores that are greater than 1 for inefficient decision-making units (as shown in Simar and Wilson (2007)); (b) the fractional regression model allows us to examine the impact of explanatory variables on either inefficiency or both inefficiency and full efficiency scores, and (c) the interpretation of coefficients on efficiency scores in the estimated fractional regression is straightforward without converting coefficient signs from positive to negative and *vice versa*.

The fractional regression model was first suggested by Papke and Wooldridge (1996) to deal with dependent variables limited to the interval of zero and unity, irrespective of whether boundary values are observed. The relative measures of efficiency obtained from the DEA approach are mapped on this interval. According to Ramalho *et al.* (2010), the fractional regression model only requires the assumption of a functional form for y that imposes the desired constraints on the conditional mean of the dependent variable (efficiency scores), which is expressed as follows: $E(y|x) = G(x\theta)$, where G(.) is a known nonlinear function satisfying $0 \leq G(.) \leq 1$, x represents a vector with external variables and θ represents a vector of parameters to be estimated. As proposed by Papke and Wooldridge (1996), this model can be estimated by the quasi-maximum likelihood based on the Bernoulli log-likelihood function as follows:

$$LL(\theta) = y_i \log[G(x_i\theta)] + (1-y_i)\log[1-G(x_i\theta)] \quad (1)$$

The estimated θ is defined as $\hat{\theta} \equiv arge\max_{\theta} \sum_{i=1}^{N} LL_i(\theta)$. Because the Bernoulli distribution is a member of the linear exponential family, the quasi-maximum likelihood estimator of θ is consistent and asymptotically normal, regardless of the true distribution of y conditional on x, provided that E(y|x) is correctly specified (Ramalho *et al.*, 2010). Further properties of this estimator can be found in Papke and Wooldridge (1996) and Ramalho *et al.* (2010).

The two alternative fractional regression models have been proposed by Ramalho *et al.* (2010) and Ramalho *et al.* (2011) to avoid biased inferences on the marginal effect of any independent variable if a prior condition is not satisfied. By raising α to any functional form $G(x\theta)$, the first generalised Type I model is given as $E(y|x) = G(x\theta)^{\alpha}$, whilst the second generalised Type II model is shown as $E(y|x) = 1 - [1 - G(x\theta)]^{\alpha}$ where $\alpha > 0$ such that $0 < E(y|x) < 1$. Both models reduce to $G(x\theta)$ for $\alpha = 1$. Accordingly, the partial effects of a unitary change in x_j are given as $\frac{\partial E(y|x)}{\partial x_j} = \theta_j g(x\theta)\alpha G(x\theta)^{\alpha-1}$ in the Type I model and as $\frac{\partial E(y|x)}{\partial x_j} = \theta_j g(x\theta)\alpha[1-G(x\theta)]^{\alpha-1}$ in the Type II model (See Ramalho *et al.*, 2010, 2011 for further detail).

The fractional regression models used in the second stage of DEA models assume that the same contextual factors influence efficient and inefficient decision-making units (DMU) in the same manner. When the probability of observing an efficiency score of unity is relatively strong, it would inevitably cause doubt about the sources of DMU efficiency that may differ from DMU inefficiency (Ramalho *et al.*, 2010). In this sense, a two-part model is applied for the DEA second stage. The first part of the model contains a standard binary choice model that dominates the probability of observing an efficient DMU. Let z be a binary indicator, then $z = 1$ for efficient DMUs and $z = 0$ for inefficient DMUs. Accordingly, the conditional probability of observing an efficient DMU is $Pr(z = 1|x) = E(z|x) = F(x\beta_{1P})$ where β_{1P} is a vector of variable coefficients and $F(.)$ is a cumulative distribution function.

The second part of the two-part model is estimated using the subsample of inefficiency DMUs and controls the DEA scores on the interval of zero and unity: $E(y \mid x, y \in [0, 1]) = M(x\beta_{2P})$, where $M(.)$ may be any of the specification considered for $E(y|x)$ in the previous section and β_{2P} is another vector of coefficients.

In order to obtain the correct specification of the functional form of the conditional mean $E(y|x)$, a correct model must be specified for $G(x\theta)$ and for both $F(x\beta_{1P})$ and $M(x\beta_{2P})$ in the one or two-part models. The RESET test can be used to detect misspecification of the general functional form. However, other tests such as p-test, GOFF-I and GOFF II tests allow us to compare nonlinear regression models or make inferences about the relevance of using either the generalised Type 1 or Type 2 models or whether it is adequate just to apply the corresponding simpler standard fractional regression model (Ramalho *et al.*, 2010, 2011).

In this article, we used the RESET test, which is a well-known test for the appropriate specification of our model; that is, whether the one-part or two-part fractional regression model should be used. Specifically, if $p < 0.05$, we reject H_0: the model is the one-part (explanatory variables influence inefficiency only) and we accept H_1: the model is the two-part (explanatory variables influence both efficiency and inefficiency). The test results showed that the one-part model is applied to both the standard and bias-corrected (bootstrapping) DEA models since $p = 0.60$ and $p = 0.91$, respectively, are much greater than $\alpha = 0.05$.

Regarding the independent variables, we employed the following factors:

(a) Administrative intensity (AI): AI is the main explanatory variable in the fractional regression model. Administration is defined as being more operational than theoretical (Rushing, 1967). In definitional terms, administration can be narrowly defined as containing 'the highest level of administrators', whereas 'a broader concept might include clerical and maintenance employees' (Boyne & Meier, 2013 p.349). This implies that different administrative categories may increase with size, whereas others may decrease. In this regard, there is no general agreement on measurement of AI. For example, AI is measured as a ratio of administrative to production workers (Pondy, 1969; Ford & Slocum Jr, 1977), as the proportion of management to administrative staff (Donaldson, 2001), as the percentage of total employees found in administrative positions (Boyne & Meier, 2013), as a form of administrative capacity (particularly in terms of human resource capacity) (Christensen & Gazley, 2008; Ryu & Christensen, 2019), as the proportion of expenditure on administration and central management to total expenditure on staff (Andrews & Boyne, 2014) and as the proportion of administrative back-office costs to total expenditure of universities (Ting *et al*., 2014).

In this article, we narrow our focus to proxy AI as the ratio of administrative costs to total annual expenditure following Ting *et al*. (2014). Administrative costs refer to annual administrative staff costs and other administration-related costs for each university. Specifically, these administrative costs consist of salaries, contributions to superannuation schemes, payroll taxes, workers compensation, long service leave expenses, non-annual leave and other employee benefits (DOE, 2022). By contrast, total expenditure comprises all costs of a university's academic operations. AI is the ratio of administrative costs to total expenditure in this regard. The average AI was 27.9% for Australian public universities during the period of 2009/10–2018/19 where specific group averages were 29.1% for RUN, 28.2% for IRU, 27.8% for NAU, 28.1% for ATN and 26.3% for Go8. This rate was slightly less than expenditure on administration allocated to academic activities in British universities at 30% (Casu & Thanassoulis, 2006). The maximum AI was 36.7%, whereas the minimum AI was 20.6% (Table 2). The empirical literature has revealed some blurring of academic and managerial identities because professional managers undertake blended or quasi-academic roles, such as managing student transitions or regional partnerships (Whitchurch, 2008; Winter, 2009). Put differently, there is no clear-cut way to distinguish professional staff from academic managers in teaching and research (such as pro-vice chancellors, deans and heads of school) who conduct both academic and professional work. Thus, it might be difficult to differentiate the administrative costs of administrative staff from administrative costs of academic staff. This difficulty should be addressed in future studies.

Regarding the specific question of scale economies in AI, it has been hypothesised that the relationship may be non-linear rather than linear in form. The empirical literature has identified an inverted U-shaped relationship between AI and organisational performance (see, for instance, Rutherford, 2016; Andrews *et al*., 2017; Ryu & Christensen, 2019), implying that as AI increases it may have a diminishing impact on organisational performance. However, in the Australian university context, the relationship between AI and university performance through can be U-shaped or inverted U-shaped depending on the different categories of university.

(b) Control variables (Z): Together with AI, exogenous factors are included in the fractional regression model to examine their impact on university efficiency. In the Australian higher education context, these variables typically consist of the staff/student ratio, the proportion of international students, the proportion of indigenous students, the proportion of Level C staff, the proportion of Level B staff and the proportion of casual staff. Dummy variables for spatial location in Queensland, Victoria and New South Wales are added to the models to examine whether there is any difference in the efficiency of universities located in different states (with the other states and territories treated as the reference). These factors have been extensively used as control variables in the Australian higher education context and their impact depends on the specific circumstances (see, for instance, Carrington *et al*., 2005; Abbott & Doucouliagos, 2009). Cognisant of the empirical literature on the Australian higher education sector, we used these control variables in our empirical analysis of universities.

Data sources for inputs, outputs and controls came from Department of Education (DOE, 2022) in a pooled structure for the period 2009/10–2018/19. Descriptive statistics of all variables are presented in Table 2.

As can be observed from Table 2, the average number of undergraduate students per university was 22,522 over the period 2009/2010–2018/19. This figure was 2.5 times higher than the average postgraduate students in the same period. By contrast, the number of students with other degrees was low, accounting for only 7.5% of total undergraduate students and around 18.3% of total postgraduate students. The number of administrative staff averaged 1570, 46% higher than the average

Table 2. *Definitions and summary statistics of variables, 2009/10–2018/19 (n = 37)*

Variable	Definition	Mean	Standard deviation	Min	Max
Dependent variable					
Efficiency score	Efficiency of universities estimated by using the standard DEA method	-	-	-	-
Inputs					
Academic staff	The number of academic staff working in individual universities	1074	635	179	3614
Non-academic staff	The number of non-academic staff working in individual universities	1570	1076	86	4509
Other expenses ($million)	The expenses excluding academic and non-academic costs used in university operations.	287	221	36	1181
Outputs					
Postgraduate students	Total postgraduate students enrolled in universities	9171	5911	1031	37,009
Undergraduate students	Total undergraduate students enrolled in universities	22,522	10,187	4723	54,043
Other degree students	Total other degrees (associate degrees, diplomas) enrolled in universities	1682	1204	82	7469
Research income category 1	Research income category 1 attracted by universities ($million)	41.8	56.28	0	220.5
Research income category 2	Research income category 2 attracted by universities ($million)	23.96	30.07	0	190.84
Research income category 3	Research income category 3 attracted by universities ($million)	26.62	35.84	0	170.31
Research income category 4	Research income category 4 attracted by universities ($million)	29.54	2.99	0	14.65
Independent variable					
Administrative intensity (%)	The ratio of administrative costs to total expenditure. Administrative costs comprise all costs outlaid on staff and other related costs serving admin operations. Total expenditure includes all costs expended by each university	27.9	2.8	20.6	36.7
Control variables					
Student-staff ratio (students)	The ratio of students to FTE staff	14.40	4.75	5.58	37.36
International students (%)	The proportion of international students	25.2	10.2	4.5	60.9
Indigenous students (%)	Proportion of indigenous students	1.4	1.2	0.05	9.7
Staff C level (%)	Proportion of C level staff & upper	41	8.1	26	73
Staff B level (%)	Proportion of B level staff	31	6.8	16	57
Casual staff (%)	Proportion of casual staff	21	13	2.3	119
QLD universities	Dummy variable, 1 for QLD universities, 0 for others	0.19	0.39	0	1

Table 2. (*Continued*)

Variable	Definition	Mean	Standard deviation	Min	Max
VIC universities	Dummy variable, 1 for VIC universities, 0 for others	0.22	0.42	0	1
NSW universities	Dummy variable, 1 for NSW universities, 0 for others	0.27	0.45	0	1

QLD: Queensland State; VIC: Victorian State; NSW: New South Wales State; Research category 1: Australian competitive grant R&D, Research category 2: Other public sector R&D, Research category 3: Industry and other R&D and Research category 4: Cooperative Research Centre (CRC) R&D.

number of academic staff at 1074. A higher number of administrative staff inevitably increases costs in maintaining academic activities relating to learning and teaching services, including the central administration of university. In addition, the research activities of universities include attracting grants from various sources, such as the Australian Research Council's (ARC) competitive grant R&D (Research category 1), other public sector R&D (Research category 2), Industry and other R&D (Research category 3) and Cooperative Research Centre (CRC) R&D (Research category 4). Among these sources, Research category 1 ranked first at $41.8 million in total, followed by Research category 4 at $29.5 million. Universities attracted $26.62 million for Research category 3 whilst Research category 2 generated on average $23.96 million for university research income. These research activities contributed significantly to the performance of universities in terms of reputation and financial support.

5. Empirical Results

We now consider the fractional regression findings on the research objectives and hypotheses presented earlier. To address the research hypotheses, we first estimated the efficiency scores of universities under both the standard and bootstrapping DEA models. On average, the estimated efficiency of Australian universities is 0.830 and 0.787 for the standard and bootstrapping models, respectively. These results are lower than the average efficiency score of Australian universities in extent studies, such as Coelli *et al*. (2005) and Duan and Deng (2016). This is probably due to the fact that our results incorporate the effects of environmental factors and cover a longer span of surveyed periods.

Table 3 presents the estimated regression results for the whole sample in terms of both standard and bootstrapping DEA efficiency, whereas Tables 4-8 contain our findings for the five categories of Australian university following the standard and bootstrapping DEA models. All models are significant at the 1% level of significance.

It can be observed from Table 3 that – for the whole sample – AI exhibits an inverted U-shaped relationship with respect to efficiency scores for both the standard and bootstrapping DEA models at the 5% level of significance. As we can see, the positive coefficient ($\beta_1 = 7.67$) of AI in the bootstrapping DEA model indicates that a 10% increase in AI leads to an increase of 0.73% in efficiency scores, *ceteris paribus*. However, when AI reaches 27.3% of the total expenditure of universities, efficiency scores start declining. The average AI of Australian universities for the period 2009/10–2018/19 is 27.9%, implying that university efficiency started to decline with respect to the level of administrative expenditure outlaid for their academic operations. As can be seen, the operational efficiency of the IRU, ATN, NAU and RUN groups may have declined because their AI was higher than 27.3%, except for the Go8 group with its AI at 26.3%.

These results contradict H_1 that holds that there is no significant relationship between AI and efficiency. Moreover, they offer support for the argument that organisations with a high degree of AI can more effectively coordinate and synchronise organisational processes and thereby improve organisational performance, but only up to a given level (Van Helden & Huijben, 2014; Walker, 2013). Thereafter increased AI induces lower levels of efficiency. This finding accords with the empirical

Table 3. *Fractional regression results of efficiency versus administrative intensity for the whole sample, 2009/10–2018/19 (n = 37 universities)*

	Standard Efficiency		Bias-corrected Efficiency†	
	dy/dx	Delta-method Std Error	dy/dx	Delta-method Std Error
Time trend	0.0059*	0.0036	0.0046	0.0034
LnAdmin Intensity	7.17**	3.69	7.67**	3.20
(LnAdmin Intensity)^2	−1.11**	0.56	−1.16**	0.48
International students (%)	−0.24**	0.09	−0.25***	0.09
Indigenous students (%)	−1.69*	0.90	−1.85**	0.73
Budget surplus (%)	0.035	0.027	0.01	0.02
Staff C level (%)	−0.29**	0.12	−0.20*	0.11
Staff B level (%)	0.36***	0.13	0.28**	0.11
Staff casual (%)	0.085	0.063	−0.030	0.038
QLD	0.052**	0.025	0.070***	0.021
VIC	−0.027	0.026	0.002	0.025
NSW	−0.009	0.020	0.029*	0.018
Constant	−81.62**	43.83	−74.51**	31.95
Observations	370		370	
R^2 (%)	0.0755		0.0833	
Loglikelihood	−124.04***		−136.41***	

***, ** and * denotes the 1%, 5% and 10% level of significance, respectively.
†Bootstrap of 2000 replications.

Table 4. *Fractional regression results of efficiency versus administrative intensity for Group of Eight, 2009/10–2018/19 (n = 8 universities)*

	Standard Efficiency		Bias-corrected Efficiency†	
	dy/dx	Delta-method Std Error	dy/dx	Delta-method Std Error
Time trend	0.0046	0.0034	−0.0029	0.0044
LnAdmin Intensity	5.28	7.38	−10.57**	4.42
(LnAdmin Intensity)^2	−0.74	1.12	1.61**	0.67
International students (%)	0.070	0.18	0.077	0.21
Indigenous students (%)	−47.95***	11.89	−41.61***	10.10
Budget surplus (%)	0.32**	0.17	−0.077**	0.034
Staff C level (%)	0.29**	0.13	0.21	0.13
Staff B level (%)	−1.07***	0.28	−0.15	0.17
Staff casual (%)	0.19	0.14	−0.23**	0.08
QLD	0.061*	0.033	0.030	0.027
VIC	0.227**	0.089	−0.090**	0.047
NSW	−0.016	0.035	−0.022	0.024
Constant	−68.09	233.64	146.05**	59.34
Observations	80		80	
R^2 (%)	0.751		0.592	
Loglikelihood	−11***		−23***	

***, ** and * denotes the 1%, 5% and 10% level of significance, respectively.
†Bootstrap of 2000 replications.

Table 5. *Fractional regression results of efficiency versus administrative intensity for Australian Technology Network group, 2009/10–2018/19 (n = 5 universities)*

	Standard Efficiency		Bias-corrected Efficiency[†]	
	dy/dx	Delta-method Std Error	dy/dx	Delta-method Std Error
Time trend	0.0086	0.0082	0.010	0.010
LnAdmin Intensity	51.22***	17.18	−59.28	42.14
$(\text{LnAdmin Intensity})^2$	−7.85***	2.66	8.69	6.34
International students (%)	−0.42	0.45	−0.21	0.64
Indigenous students (%)	−44.93***	8.15	−13.70	14.55
Budget surplus (%)	0.50***	0.08	0.33***	0.09
Staff C level (%)	−0.33	0.40	−0.27	0.38
Staff B level (%)	1.07***	0.37	0.96***	0.36
Staff casual (%)	0.53	0.37	0.11	0.33
QLD	-	-	-	-
VIC	0.047	0.036	0.050	0.049
NSW	−0.272***	0.056	−0.143**	0.059
Constant	−749.22***	261.12	783.54	528.09
Observations	50		50	
R^2 (%)	0.777		0.629	
Loglikelihood	−12.46***		−14.82***	

***, ** and * denotes the 1%, 5% and 10% level of significance, respectively.
There are no ATN universities in Queensland.
[†]Bootstrap of 2000 replications.

literature on the relationship between AI and university performance (see, for instance, Rutherford (2016) and Andrews *et al*. (2017)).

In order to address research hypothesis H_2, we stratified the whole sample into five groups of universities comprising the G08, ATN, IRU, RUN and NAU and then regressed efficiency scores against AI in the presence of control variables. The estimated results are presented in Tables 4–7 for the standard and bias-corrected efficiency scores. The estimated models are significant at the 1% level.

In the standard efficiency model, AI has a significant impact on efficiency for the RUN, ATN and NAU groups, but not for the Go8 and IRU groups. The relationship between AI and the standard efficiency scores is U-shaped for RUN, whereas this relationship is inverted U-shaped for the ATN and NAU. This implies that AI has a negative effect on the performance of RUN universities. However, AI enhances the performance of ATN and NAU groups and this influence has driven the positive impact of AI on the standard efficiency scores of the whole sample.

This curvilinear relationship is similar to the bias-corrected efficiency model. AI significantly affected bias-corrected efficiency in the Go8, RUN and NAU categories at the 1% level of significance. We can see that the relationship between AI and efficiency scores is U-shaped for the Go8 and RUN groups, whereas this relationship is inverted U-shaped for the NAU. Specifically, a 10% increase in AI leads to a decline of 1% and 1.16% in the efficiency scores of the Go8 and RNU groups of universities, respectively. However, the NAU group increased by 1.1% in their efficiency score with respect to a 10% increase in AI. The inverted U-shaped relationship has driven the impact of AI on the performance of Australian universities across the entire sample. We note that the association between AI and the bias-corrected efficiency scores is not statistically significant for the IRU and ATN groups. As we can see, AI reduces operational efficiency for both the Go8 and RUN groups, whereas AI significantly improves the performance of the NAU group. Based on these findings, H_2 is rejected: there is a

Table 6. *Fractional regression results of efficiency versus administrative intensity for Innovative Research Universities group, 2009/10–2018/19 (n = 7 universities)*

	Standard Efficiency		Bias-corrected Efficiency†	
	dy/dx	Delta-method Std Error	dy/dx	Delta-method Std Error
Time trend	−0.0024	0.0084	0.011	0.0090
LnAdmin Intensity	0.33	20.65	10.80	17.14
(LnAdmin Intensity)^2	−0.02	3.10	−1.55	2.58
International students (%)	−0.55***	0.17	−0.50***	0.17
Indigenous students (%)	6.80***	1.88	2.23	1.75
Budget surplus (%)	0.16**	0.078	0.070	0.067
Staff C level (%)	−0.64**	0.29	−1.01***	0.34
Staff B level (%)	0.36	0.40	0.28	0.46
Staff casual (%)	1.15***	0.34	0.38	0.25
QLD	0.030	0.041	0.15***	0.049
VIC	0.034	0.066	0.072	0.064
NSW	0.0030	0.066	0.150*	0.083
Constant	−4.41	202.89	−100.83	156.07
Observations	70		70	
R^2 (%)	0.4666		0.392	
Loglikelihood	−25.05***		−26.78***	

***, ** and * denotes the 1%, 5% and 10% level of significance, respectively.
†Bootstrap of 2000 replications.

significant difference between various types of university with respect to the curvilinear association between AI and university efficiency. This result accords with both public choice theory as well as recent empirical studies on AI and organisational performance in the higher education sector (see, for instance, Andrews *et al.* (2017) and Rutherford (2016)).

Controls for demographic factors are common in the empirical literature (see, for example, Carrington *et al.*, 2005; Tran & Villano, 2021). These variables have significantly influenced the performance of Australian higher education institutions (see, for instance, Carrington *et al.*, 2005). Our findings show the differential impact of these control variables on the five groups of university in terms of the standard and bias-corrected efficiency models. As we can see, the impact of control variables on efficiency scores in the presence of AI is mixed throughout Tables 3–8 for the whole sample and the five university groupings. This implies that while the effect of AI on efficiency scores plays an important role in university performance, the influence of contextual factors should be of interest given that they fall outside the control of university managers.

6. Discussion of Results

Efficiency refers to the ability of single firm to produce maximum outputs at the existing levels of the inputs (Farrell, 1957; Fried *et al.*, 2008). In the university context, administrative intensity represents opportunity costs in terms of foregone production activities (Leslie & Rhoades, 1995). An intensification in administrative intensity through administrative staff growth could thus lead to a decline in efficiency given that the output produced does not increase proportionately. This can result in a decline in university performance (Van Helden & Huijben, 2014). Conversely, larger central bureaucracies generated by administrative staff growth may result in the superior coordination of more complex tasks, thereby increasing organisational efficiency (Van de Ven *et al.*, 2013; Andrews *et al.*, 2017). However, this curvilinear relationship between administrative intensity and efficiency

Table 7. *Fractional regression results of efficiency versus administrative intensity for Regional Network University group, 2009/10–2018/19 (n = 7 universities)*

	Standard Efficiency		Bias-corrected Efficiency†	
	dy/dx	Delta-method Std Error	dy/dx	Delta-method Std Error
Time trend	−0.017**	0.0085	−0.017**	0.0067
LnAdmin Intensity	−16.50**	6.78	−12.26**	5.36
(LnAdmin Intensity)^2	2.53**	1.03	1.89**	0.81
International students (%)	0.30	0.28	0.29	0.21
Indigenous students (%)	4.30	4.69	6.84*	3.66
Budget surplus (%)	−0.046***	0.012	−0.049***	0.011
Staff C level (%)	−0.03	0.26	−0.18	0.20
Staff B level (%)	0.63**	0.30	0.75***	0.23
Staff casual (%)	0.12	0.093	0.054	0.049
QLD	−0.019	0.052	−0.013	0.042
VIC	−0.20	0.16	−0.16	0.12
NSW	-	-	-	-
Constant	216.43**	93.68	127.5**	58.76
Observations	70		70	
R^2 (%)	0.66		0.751	
Loglikelihood	−20.23***		−23.45***	

***, ** and * denotes the 1%, 5% and 10% level of significance, respectively.

There are no RUN universities in other states, thus RUN universities in NSW is treated as the reference.

†Bootstrap of 2000 replications.

does not continue indefinitely. In terms of economic perspective, diseconomies of scale exist when long-run average costs rise as the quantity of output increases (Hubbard *et al.*, 2017). In the university context, the operational efficiency would decline when the rising level of administrative intensity (embedded in administrative staff growth) occurs more rapidly than the level of academic output produced by universities.

An association between AI and organisational performance has been found in the empirical literature (see, for example, Carillo & Kopelman, 1991; Boyne & Meier, 2013; Rutherford, 2016; Andrews *et al.*, 2017, Ryu & Christensen, 2019). It has been argued that growth in the size of bureaucracy can lead to inefficiency in operations due to excess administrative personnel (Caplow, 1957; Parkinson, 1957; Merton, 1968). However, a positive relationship between AI and organisational performance was found in manufacturing firms (Holland, 1963; Pondy, 1969) and in tertiary education institutions (Rutherford, 2016; Andrews *et al.*, 2017; Ryu & Christensen, 2019). This positive relationship occurs as an inverted U-shaped relationship implying that a rise in AI initially enhances organisational performance and thereafter organisational performance declines when AI exceeds its optimum level (Rutherford, 2016; Andrews *et al.*, 2017; Ryu & Christensen, 2019).

Our findings are in line with the literature in that there is a significant relationship between AI and university efficiency (H1 is rejected) and that this relationship is positive and takes an inverted U-shape for the whole sample, implying that the efficiency of Australian universities increases when AI rises. These results support the structural contingency theory prediction that organisations with a high degree of administrative intensity can more effectively coordinate and synchronise organisational activities and thereby improve organisational performance (Walker, 2013; Van Helden & Huijben, 2014; Tran & Dollery, 2022). However, the curvilinear relationship between administrative intensity and university efficiency indicates that when the aggregate demand for academic services

Table 8. *Fractional regression results of efficiency versus administrative intensity for Non-Aligned University group, 2009/10–2018/19 (n = 10 universities)*

	Standard efficiency		Bias-corrected efficiency	
	dy/dx	Delta-method Std Error	dy/dx	Delta-method Std Error
Time trend	0.0091	0.0059	0.013**	0.0051
LnAdmin Intensity	14.90***	4.31	11.53**	4.60
$(\text{LnAdmin Intensity})^2$	−2.27***	0.66	−1.76**	0.70
International students (%)	−0.037	0.17	−0.22	0.17
Indigenous students (%)	6.52***	2.12	4.47**	2.01
Budget surplus (%)	0.14*	0.082	0.11	0.094
Staff C level (%)	−0.57***	0.21	−0.45**	0.18
Staff B level (%)	−0.20	0.41	−0.06	0.33
Staff casual (%)	0.85***	0.30	0.35***	0.13
QLD	0.093*	0.056	0.18***	0.05
VIC	−0.049	0.039	0.008	0.037
NSW	−0.13***	0.044	−0.03	0.038
Constant	−152.41***	45.95	−103.39**	42.42
Observations	100		100	
R^2 (%)	0.5398		0.50	
Loglikelihood	−34.46***		−37.48***	

***, ** and * denotes the 1%, 5% and 10% level of significance, respectively.

rises in proportion to student size, a decrease in administrative intensity would be necessary to maintain the operational efficiency of universities. Our findings indicate that the administrative intensity of universities should be at 27.3% at maximum because beyond this threshold, university efficiency would decline due to the inefficient usage of administrative resources, even when the number of students continues to increase. For the period of 2009/10–2018/19, the average administrative intensity of public universities in Australia was 27.9% (or slightly higher than the administrative intensity threshold at 27.3%) while the student growth was approximately 33.2% during this period. Given the increasing financial pressure on public universities over recent years, especially in the COVID-19 pandemic period when Australian universities have faced a revenue shortfall (Universities Australia, 2020), this has raised concerns over outlays on administrative resources and posed policy questions over possible scale economies in administrative intensity at universities (Rutherford, 2016; Ryu & Christensen, 2019; Tran & Dollery, 2022). This suggests that universities need to have a more appropriate policy for using administrative resources through more reasonable growth in administrative staff and related administrative activities.

We stratified the whole university sample into five group (Go8, ATN, IRU, RUN and NAU) to secure empirical insights into differences in the impact of AI on the efficiency of university groups with respect to these five categories. Our findings showed that AI significantly affected the efficiency of Go8, RUN, ATN and NAU rather than IRU (H2 is accepted). The influence of AI was present in a U-shaped form for the Go8 group with respect to bias-corrected efficiency and for the RUN group in both the standard and bias-corrected efficiencies at the 5% level of significance. This implies that the efficiency of these groups declines when back-office costs increase. Put differently, the larger the organisation, the greater the bureaucratic problems involved in monitoring and control, as public choice theory suggests (Bohte, 2001; Boyne & Meier, 2013; Boon & Verhoest, 2014). Both of these university groups should consider reducing administrative costs by means of decreasing aggregate administrative size where necessary, especially for the RUN group, where the number of enrolments is much lower than in the Go8 group. By contrast, AI has an inverted U-shaped impact on the standard efficiency of the ATN group and on both the standard and bias-corrected efficiency of the NAU group. In addition, the influence of AI on the efficiency of the ATN and NAU groups has driven the impact of AI on the efficiency of the whole university sample. That is, an increase in AI enhances organisational performance. However, if AI continues to increase, it can then induce a decline in efficiency. It is noted that AI had no significant influence on the performance of the IRU group.

With respect to the above analysis, we can thus conclude that the influence of administrative intensity on the efficiency of public universities is heterogeneous among the five university groups. This is primarily because each university group has its own research and development objectives that would affects its ability efficiently deploy financial resources to administrative activities. In addition, the operational efficiency of different types of university varies due to differences in non-discretionary environmental characteristics that generally fall outside the control of university management (Carrington *et al*., 2005; Tran & Villano, 2021; Tran & Dollery, 2022).

7. Concluding Remarks

In this article, we have investigated the influence of AI on the performance of Australian universities accounting for exogenous influences and biases from unobserved disturbances. The findings that emerge from our estimations shed light on our two research hypotheses.

Firstly, AI positively affected the efficiency of universities for the whole sample to a decreasing degree. This relationship is curvilinear and significant at the 5% level of significance, implying that although AI currently contributes to the performance of Australian universities as a whole, to maintain their operational efficiency, they should decrease the proportion of aggregate expenditure devoted to administrative intensity in the long run. Given the period 2009/2010–2018/2019, the average administrative intensity of a given university should be 27.3% at maximum (the so-called threshold rate). Although the difference between the existing administrative intensity and the threshold rate was minimal (27.9% versus 27.3%), beyond this threshold rate, an increase in administrative intensity would lead to a decline in the efficiency of universities. In addition, the DEA efficiency results showed that there has been surplus in using input resources in Australian public universities over the period in question. Administrative staff employed exceeded 4% over total current administrative staff whilst the academic staff and other expenses were over 3% and 2%, respectively. In order to obtain full efficiency, universities need to reduce the number of administrative staff by 60, academic staff by 31 and other expenses by $5million (see Table A1 for more detail). To this end, universities could potentially initiate a process of sharing and aggregating administrative services and/or remove unnecessary units to avoid bureaucratic problems involved in monitoring and control. This would improve economies of scale (Boyne & Meier, 2013). According to Arena *et al*. (2009), although university reputation and teaching performance have remained a key to attracting students, student support services are also important as facilitators in the learning and teaching process. Thus, restructuring and rearranging administrative activities is necessary to maintain effective service provision whilst still retaining operational efficiency in universities. It is widely recognised that financial efficiency is vital for many university stakeholders, given the complex university stakeholder environment (Chapleo & Simms, 2010, Harrison & Wicks, 2013).

Secondly, there was a statistically significant difference in the impact of administrative intensity on the efficiency scores of the five different university groups. Administrative intensity positively affected the efficiency of the ATN and NAU groups more than the other university groups. Moreover, this influence has driven the impact of administrative intensity on universities for the whole sample. As discussed earlier, differences in development strategies of the different university groups could potentially influence the degree of administrative intensity in their academic operations and thereby the overall efficiency of universities. In addition, we found that contextual variables affected the efficiency of universities and that the influence of these variables was significant in both the bias-corrected and standard efficiency models.

Our findings have contributed to the existing empirical literature on Australian higher education in several respects. First, we have demonstrated the importance of administrative intensity for university efficiency. The impact of administrative intensity, together with non-discretionary factors, constrained the operational efficiency of universities at a more general level. Our findings demonstrate that public policy formulation in higher education systems should be informed by an understanding of the empirical characteristics of the specific higher education system in question. For instance, as we have shown, the determinants of university efficiency affect not only the categories of students and university functions, but also human resource management. Finally, in methodological terms, our article has broken new ground with the application of a fractional regression model integrated into a second stage bootstrapped DEA model to generate a more robust estimation in order to investigate the impact of various factors, like administrative intensity, on the performance of universities. This approach can be generalised to different contexts not only in the empirical analysis of universities, but of other kinds of organisation as well.

Although our article has provided insightful results on the relationship between administrative intensity and university efficiency, there is an urgent need for further empirical research into the factors that can potentially depress operational efficiency in higher education systems. Although university expenditure, such as outlays on university administration, is a key factor in operational efficiency, other dimensions of higher education require further empirical research, including the ability to deal with non-discretionary variables.

Conflict of Interest Statement

There is no conflict of interest in this article.

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Data Availability Statement

Data can be accessed publicly at Department of Education at https://www.education.gov.au/higher-education-statistics.

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Appendix

A.1 The data envelopment analysis for the local government analysis

Following Banker *et al*. (1984), suppose that each university (U) uses a vector of m discretionary inputs $X = (x_1, \ldots, x_m)$ to produce a vector of s outputs $Y = (y_1, \ldots, y_s)$. Inputs and outputs for $U_j (j = 1, \ldots, n)$ are given by $X_j = \left(x_{1j}, \ldots, x_{Mj}\right)$ and $Y_j = \left(y_{1j}, \ldots, y_{Sj}\right)$.The VRS empirical production possibility set is given by

$$P_v = \left\{ \begin{array}{c} (X, Y);\ \sum_{i=1}^{N} \lambda_i y_{si} \geq y_s,\ \sum_{i=1}^{N} \lambda_i x_{mi} \leq x_m,\ \sum_{i=1}^{N} \lambda_i = 1, \lambda_i \geq 0 \\ s = 1, \ldots, S; m = 1, \ldots, M; i = 1, \ldots, N \end{array} \right\}$$

where λ_i are the intensity variables to contract or expand the observed operations of each university $i\ (i = 1, \ldots, N)$ to construct convex combinations of the observed inputs (x_i) and outputs (y_i). Relative to the reference technology P_v constructed in (1), the estimator of the efficiency score θ can be obtained by solving the following programming problem:

$$\hat{\theta}_{VRS} = max\left\{\theta > 0 | y_s \geq \sum_{i=1}^{n} \lambda_i y_{si}, \theta x_m \leq \sum_{i=1}^{n} \lambda_i x_{mi}, \sum_{i=1}^{n} \lambda_i = 1, \lambda_i \geq 0, i = 1, \ldots n\right\}$$

where $\hat{\theta}_{VRS}$ is the projection of an observed each university (x, y) to the efficient frontier and provides the initial technical efficiency of the i^{th} university. For all $(x, y) \in L_v$, $\hat{\theta}_{VRS} = 1$, each university is fully technically efficient; alternatively, if $\hat{\theta}_{VRS} < 1$, it is inefficient.

Table A1. *DEA Input slack to be reduced for the full efficiency of Australian public universities*

Year	Academic staff			Administrative staff			Other expenses ($million)		
	Actual	Target	Slack	Actual	Target	Slack	Actual	Target	Slack
2009/2010	948	909	39	1551	1441	110	212	211	1
2010/2011	974	930	44	1597	1552	45	226	222	5
2011/2012	1014	969	45	1654	1558	96	244	242	2
2012/2013	1035	997	39	1557	1477	81	259	259	0
2013/2014	1044	1007	37	656	637	19	273	271	1
2014/2015	1069	1046	24	1779	1694	85	292	292	1
2015/2016	1094	1072	22	1795	1726	69	309	308	1
2016/2017	1120	1098	21	1820	1771	49	330	307	23
2017/2018	1206	1187	19	1622	1585	37	347	342	5
2018/2019	1236	1217	19	1665	1654	11	381	374	7
Average	1074	1043	31	1570	1509	60	287	283	5