Author/s:
Moore, K;Croucher, G;Coates, H

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Productivity and policy in higher education

Kenneth Moore[1*], Gwilym Croucher[1], Hamish Coates[*]

Tsinghua University

[*]Corresponding author: Coates, Tsinghua University, Email: hamishcoates@tsinghua.edu.cn

ABSTRACT

Understanding and improving the performance of public higher education institutions is a matter of growing interest to university and government leaders. To this end, this paper surveys dimensions of recent approaches to productivity measurement in higher education, illustrating trends, limitations and developments, and exemplifies these with reference to Australian universities. The paper closes by discussing policy considerations which would help augment the design of policy, making comment on the implications for performance incentivised funding of higher education.

KEYWORDS: higher education; productivity; funding; performance

1. The need to study productivity in higher education

Understanding and improving the performance of public higher education institutions is a matter of growing interest to university and government leaders. For their part, university leaders have an evident, albeit often difficult to realise, interest in ensuring that available resources are converted as efficiently as possible into the highest-quality outcomes. As the main purchases and often consumers of higher education services, governments too have sought to shape productivity through a range of performance measures and schemes. In a resource-abundant world, these and other perspectives would align in aspiration and practice. In such a world, governments would allocate resources in ways that allowed optimised university operations and performance.

[1] Centre for the Study of Higher Education, University of Melbourne, Victoria, 3010, Australia; Coates, Institute of Education, Tsinghua University, Beijing, China.

Public policy and financing are contingent, affected by a host of political, historical and cultural factors. While higher education consumes a growing portion of expenditure in most advanced economies, the study of higher education finance is in its infancy (Lepori & Jongbloed, 2018). Even if government allocations could be optimised, their utility would hinge on, and may be undermined by, complex and frequently non-financial arrangements within institutions. Institutional management, for its part, at times remains far from an exact science, involving many forms of arbitrage and opaque allocation (eg Lombardi, 2013; Ginsberg, 2011). Such uncertainties may explain why the performance-based funding schemes attempted by various governments have delivered varying levels of success (Jongbloed & Vossensteyn, 2001; Tandberg and Hillman 2013; Dougherty et al., 2013; Dougherty & Natow, 2015).

The limited success of government policies designed to promote higher education performance reflects the challenge in accurately measuring university productivity. If university, government and community interest in optimising funding and performance is to be met, then there is a need for more technically and practically cogent perspectives on finance and performance, which are far more sensitive to how universities work. Specifically, this goes to the need to progress perspectives, methods and ultimately practices regarding university productivity. The strengths and limitations of different approaches to measuring productivity is all the more important in the context of higher education funding policy that is performance driven, which can only be as effective as the instruments employed.

This paper surveys dimensions of recent approaches to productivity measurement, making comment on the policy implications for performance incentivized funding of higher education. The paper continues in the next section with discussion of different approaches to productivity assessment in higher education, illustrating trends, limitations and developments. Next, it exemplifies these approaches with reference to Australian universities. The paper closes by discussing policy considerations which would help augment the design and outcomes of policy.

2. Approaches to productivity assessment

Before examining specific approaches, it is worth signalling that differences in the interpretation of the concept of productivity and the use of particular metrics reflects broader epistemological questions around the inputs and outputs of higher education. The term ‘productivity’ is also commonly pre-loaded with context and connotation depending on who is using it, and whether they are inside or outside higher education institutions. Ghobadian and Husband (1990) suggest that the array of technical definitions of productivity may be reduced to three broad conceptualisations. As a ‘technological’ concept, it can be understood narrowly as the relationship between ratios of output to the inputs used in production. As an ‘engineering’ concept, it highlights the relationship between the actual and the potential output of a process. As a concept familiar to economic and management research, the measurement of productivity is more concerned with the efficiency of resource allocation. With reference to these conceptual perspectives, Massy (2016; 2017) distils three analytical paradigms and foci for higher education: value-creation and an emphasis on teaching

and research output and its quality; efficiency of outputs relative to inputs and process innovation; and financial returns (or margin) via revenue minus costs. Each paradigm implies different treatment of inputs and outputs. Determining which measures are an appropriate fit for context and purpose must take into consideration base level assumptions about the purpose of analysis, where reconciling alternative foundational understandings of the concept can be difficult. While it is beyond the scope of this paper to examine in detail what different fundamental assumptions imply for each formulation and approach, it is important to signal that due to the differences, analyses may conflict or not be directly comparable.
As such background portends, multiple techniques have been developed to examine productivity in higher education. Singh, Motwani and Kumar (2000) summarize three umbrella methods to estimate productivity: linear programming, econometric models, and index measures. The most common in higher education is a linear programming approach: Data Envelopment Analysis (DEA). This non-parametric technique allows estimation of the production frontiers for a set of inputs and outputs. Also common is stochastic frontier analysis (SFA), a parametric econometric modelling technique. Econometric models typically estimate production functions using regression analysis. The Törnqvist Index (TI), an index measure, has also been used to measure productivity change over time. The TI measures changes in productivity by dividing changes in a composite output variable by changes in a composite input variable. Index measures have been the least common in higher education, though they are growing in popularity perhaps given popularity in other industries (Singh, Motwani & Kumar, 2000). Index measures are espoused by the Australian Bureau of Statistics (2012), the United States Bureau of Labor Statistics (2007) and the Organisation for Economic Operation and Development (OECD) (2001). Carrington, Coelli & Rao (2005) explain inherent difficulties of employing indexing methods in higher education because of the multi-input and multi-output nature of production, and the fact that higher education outputs are best represented as non-priced entities. The combination of these two factors make data elements difficult to aggregate in a single metric. DEA solves the aggregation problem, which serves as the principal reason why DEA has become the default option for many people undertaking university productivity analysis. DEA is able to aggregate multiple inputs and outputs without the need for explicit price information by utilising implicit characteristics associated with the shape of the dataset (Cooper, Seiford & Tone, 2007). This allows for measurement to take place without researchers having to impose personal value judgments on individual outputs (Cooper, Seiford & Tone, 2007). This situation, of course, does not mean that judgments about the interpretation of variables and results are not being made, rather than these are outsourced to the algorithm.

Recent developments have been made in specifying a TI model for higher education. A model advanced by the United States National Research Council was designed for the education function of universities (Sullivan, Mackie, Massy & Sinha, 2012). Its approach focuses on the teaching activity of universities, although it is amenable to modification to allow for incorporation of research outputs and generalisation across cultures (e.g. Coates, 2017; Moore, Coates & Croucher, 2018). A strength of analyses conducted with indexing methods like TI is that they focus less on frontier estimation and rank-order comparisons of institutions' technical efficiencies, and more on relationships between data elements and measured results and on threshold ranges for plausible productivity portrayals. TI results are best used to visualise the shape of institutional productivity trends over time and to understand relationships between data elements used in calculation. The technique can be used to provide a range of portrayals based on alternative treatments of data. TI is readily used to understand dynamics of relationships between inputs and outputs over time and the extent to which different institutions are sensitive to different treatments of data. Sensitivity to data aggregation can reveal characteristics of institutional functioning and can highlight the diversity of institutional approaches to higher education provision across a system. Limitations of the technique include its inability to estimate efficiency frontiers, and that value weights on data elements must be imposed by researchers based on either outside information or based on analytical objectives.

Conversely, the value of DEA is in its estimation of efficiency frontiers. It allows for a characterisation of the potential for an institution to close the gap between its current productivity and its maximum achievable productivity. The treatment of data across institutions is not consistent and often different for each institution, with value weighting schemes not always known or reported because the weights occur as shadow variables within the DEA algorithm. The approach is argued, however, to minimize controversy because each institution in a dataset is assigned its maximum possible score given available data observations. A recent DEA study on Australian universities acknowledges how optimal portrayals can produce unrealistic results in higher education and confronts the problem by imposing stricter limits on how data elements are treated during calculation (Szuwarzyński, 2018). While the techniques uses empirical methods to assign value weights to data elements, it is limited by assumptions of institutional homogeneity (Dyson et al., 2001) and its more opaque algorithms. Details about the treatment of data are not always exposed and may include inconsistent representation of relationship dynamics between inputs and outputs over time.

As well as the particular modelling approach employed, the choice of data to analyse university productivity affects interpretation of any given calculation technique. Trade-offs in analytical precision and utility exist with any single specification of institutional inputs and outputs. Dozens of measurable indicators could serve as inputs or outputs in an analytical framework (Miller, 2007). Choices, though, often rest on what data is currently accessible, rather than on precise analytical objectives. To compensate for such pragmatism, Wolszczak-Derlacz (2013) illustrates the value of synthesising the measurement results from four different input-output frameworks. Such integrated analysis reveals dynamics and relationships between variables that would have otherwise been lost with single input-output model.

Along with uncertainties around perspectives, models and data, the ad hoc nature of technical productivity research in higher education poses challenges for establishing a foundational body of knowledge and for making improvements to practice. Complicating matters further is that determinations about whether particular data elements should be specified as inputs or outputs depends on context and interpretation. For example, Wolszczak-Derlacz (2013) specifies students as inputs, but Yaohua, Muyu, Weihu and Xianyu (2018) designate students as outputs. Students may intuitively seem like inputs because they are admitted to an institution as intended participants of a planned educational process. Alternatively, students may be considered outputs if they serve as a proxy for the scale of educational services delivered by an institution (Sullivan et al., 2012).

Uncertainties such as those discussed here have resulted in different approaches to evaluating higher education productivity. By way of illustration, Table 1 lists 20 productivity analyses within higher education since the mid-2000s, mapping these by indicators and ratio calculation techniques. Most of the diversity emerges with output choice because input choices are generally limited to expenditure and student and staff data. Across all studies, only two models use common outputs and calculation technique. With so much diversity, the relative value of different methods in context can be difficult to judge.

The range of potential outputs shown in Table 1 is indicative of the multiple paradigms for understanding productivity mentioned above. Data selection serves as the expression of the operative analytical paradigm and what researchers and stakeholders have deemed important for representing performance in context. Nazarko (2014) considers student achievements as educational outputs by tracking scholarship recipients and study abroad participants. Olariu & Brad (2017) consider enrolment numbers and government revenue. Each speaks to a different realm of performance and priorities, but both do so under the guise of productivity, and each compute results using DEA. There is more consensus around measuring research output via academic publications, but methods for doing so vary. A host of other data elements also indicate the production of knowledge and its impact.

Table 1: Productivity models in higher education

		Calculation technique																			
Indicator	**Variable**						**Linear programming**								**Econometrics**				**Indexing**		
Education	Student load					**X**			**X**				**X**	**X**				**X**	**X**		
o	Student enrolmen	**X**	**X**	**X**	**X**				**X**										**X**		

utputs	t																			
	Student achievements							X										X		
	Degree completions		X	X		X				X	X	X			X	X		X		
	Adjusted credit hours																		X	X
	Exceeded or passed credits													X						
	Graduate employment						X	X										X		
	Revenue from government	X		X																

	Revenue from student fees				X																
	Publications	X			X	X	X		X		X			X					X		X
	Citations	X																	X		
	Institutional rankings									X											
Research outputs	Research degrees awarded																		X		X
	Patents																		X		
	Research income	X		X							X	X	X	X				X	X		X
Micellaneo	Reputation	X																			

us

3. Assessing higher education productivity in Australia

Australian higher education is fertile context for exploring productivity given the sector size, data transparency and institutional variation. Australian universities have been operating under a relatively constant national policy framework since the mid-2000s (Goedegebuure & Marshman, 2017). Several studies have been conducted to estimate the productivity of Australian universities since the late 1990s (Abbott & Doucouliagos, 2003; Carrington et al., 2005; Moore, Coates and Croucher, 2018; Moradi-Motlagh, Jubb & Houghton, 2016; Worthington & Lee, 2008). The discussion in these analyses are generally limited to implications for the practice of measurement, with some speculation about contextual drivers of observed trends. The authors rightly address the limitations of higher education productivity measures and refrain from using results to prescribe even technical policy recommendations. Incremental improvement to measurement practices have resulted, however, and the accumulation of results on the topic over time carries potential to shed light on key policy issues.

To further illustrate the variation between approaches, Table 2 shows results from two productivity analyses on the same set of Australian university data for the period 2007 to 2013. The data includes one input and two output measures: operational expenditures (input), student load (output) and research publications (output).The first ranking uses TI methods and a value weighting scheme that treats education and research outputs equally, as reported in Moore, Coates and Croucher (2018: 11). The second uses DEA methods, which computes a value weighting scheme to portray each institution in its most optimal light given available data, as reported in Moradi-Motlagh, Jubb & Houghton (2016). The rank ordering of universities in terms of positive productivity change experienced over the period varies greatly. Further, given the complexity of higher education provision, neither equal nor optimal treatment of data is by default the most appropriate performance portrayal. Each weighting scheme is arbitrary with respect to broader operational and strategic contexts.

Table 2: Rank ordering of Australian university top five productivity change for 2007 to 2013 using TI and DEA methods

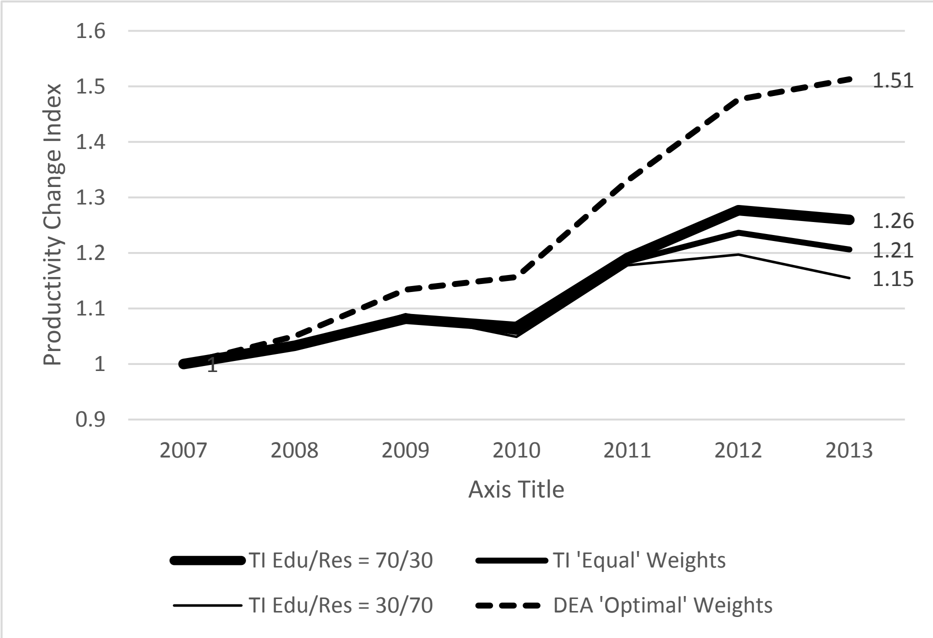
TI ranking	DEA ranking
1. Swinburne University of Technology	1. Murdoch University
2. Murdoch University	2. University of New South Wales
3. University of Western Australia	3. University of Western Australia
4. Central Queensland University	4. University of Canberra
5. University of Tasmania	5. University of Melbourne

Figure 1 expands upon the comparison by illustrating productivity change dynamics across the period for three of the universities listed above, Murdoch University, The University of New South Wales and Swinburne University of Technology. These examples reveal the variability hence uncertainty in productivity estimates given different models and assumptions. Again, the DEA model aggregates all data elements by assigning weights, as to maximize individual portrayals of productivity change with respect to other institutions in the dataset. Value weights on the data elements are not known, and may vary from one time-point to the next, and likely vary per institution. Productivity change figures are taken from the Appendix of Moradi-Motlagh, Jubb & Houghton (2016). The TI model provides three alternative weighting schemes, each of which remains consistent over the period and operates consistently on all institutions. The TI model assigns value weights only to the output elements, such that the research and education outputs are (1) weighted equally, (2) weighted with emphasis on education, and (3) weighted with emphasis on research. The estimates reveal a distribution of plausible productivity change portrayals based on the data considered.

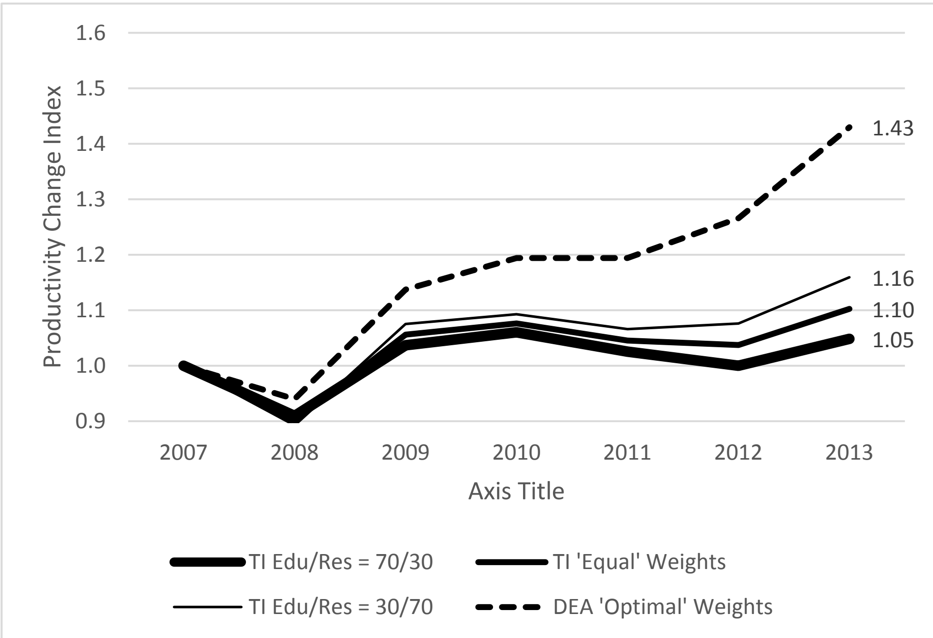
Figure 1: Comparison of productivity change estimates for Murdoch University

Source (Moore, Coates and Croucher, 2018; Moradi-Motlagh, Jubb & Houghton, 2016)

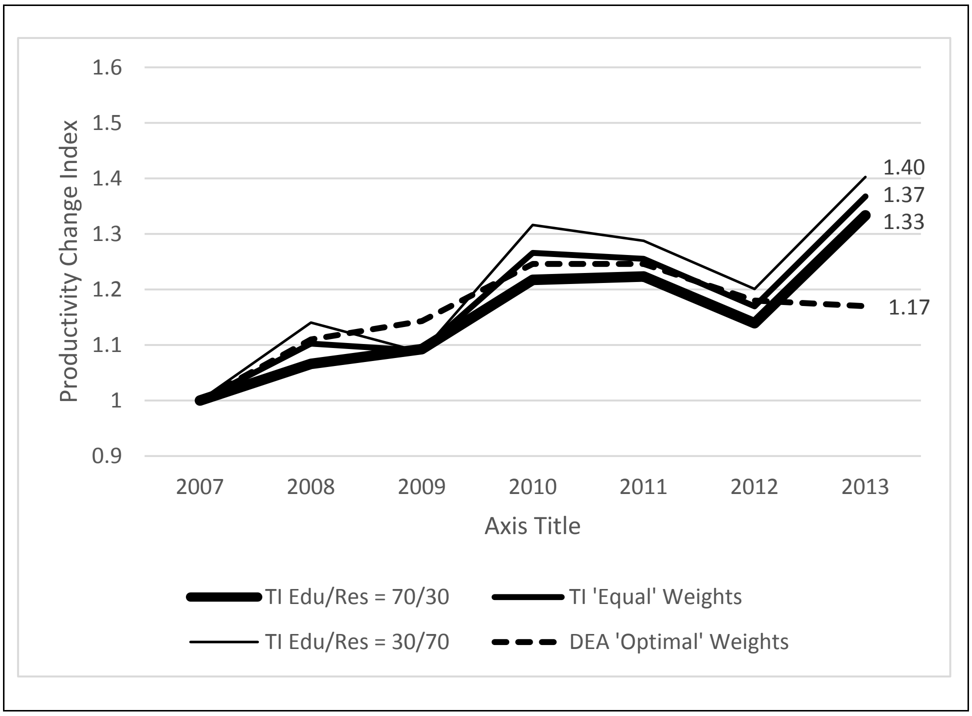
Murdoch University



The University of New South Wales



Swinburne University of Technology



The distribution of portrayals could in itself be modelled to obtain more robust statistics, but the exercise highlights the inherent indeterminacy in such analysis. For Murdoch University and The University of New South Wales, it is apparent that the DEA algorithm served to emphasise either education or research outputs to a greater extent than any of the TI models. For Swinburne, reverse engineering the DEA algorithm to determine how weights were assigned is more difficult. Additionally, this collection of estimates necessarily ignores more nuanced within-institution contexts. These contexts may or may not serve as constraints that diminish the range of potential interpretations of measured results.

That TI and DEA results differ is unsurprising. Each method has a different utility and opportunity for insight. As previously noted, TI results help clarify the relationship between data elements over time, whereas DEA through estimation of efficiency frontiers help make clear the contrast between measured and maximum achievable productivity. What their comparison reveals is that a complex and contradictory story quickly emerges. One consistent finding is the extent to which positive productivity portrayals in Australia depend upon the gains being realised in research, as opposed to education. The role of research productivity driving the sector was observed in Worthington and Lee (2008). The authors hypothesised, however, that research gains from 1998 to 2003 were likely due to the elimination of inefficiency and were likely unsustainable trends. Increasing research productivity and stationary education productivity continues, however, to define the behaviour of the sector, and the momentum does not appear to be lessening (Moore, Coates and Croucher, 2018). These observations run in line with some recent assessments, which claim the behaviour is more inherent to Australian higher education and is driven by unbalanced incentive structures. The Productivity Commission (2017) asserts that teaching and research in Australian higher education are not best characterised as a nexus, but rather as two separate functions that compete for time and resources, as evidenced by common practices among universities in subsidising research activities with revenues generated by education and course fees.

The analysis of Australian universities shows the extent that institutional performance trends may differ depending on which data elements are emphasised in a calculation. Further, the range of plausible productivity interpretations varies in size per institution. This is because any aggregate university indicator is packed with hidden and measurable information that is open to interpretation. Student progression and retention over time, for example, is one indicator among many that affects the final productivity portrayal in Moore, Coates and Croucher (2018). But even examining the extent to which this indicator is associated with productivity or how much it varies between institutions still says nothing about why students drop out—which may or may not relate to the quality of the educational experience.

4. Implications for design of funding policies

From the perspective of those charged with public funding for higher education, productivity measurement is only as valuable as its effectiveness in guiding the design of allocation mechanisms that enhance performance. As the brief survey here of productivity measurement in higher education shows, there are strengths and weaknesses to different approaches, and that a multifaceted and inconsistent story can quickly emerge. In light of this challenge, this paper notes some implications for designing government funding to enhance university performance.

Where policymakers wish to enhance university productivity, the policies selected usually prioritise a particular aspect of performance to incentivise or punish. Combined with the difficulty and cost in collecting data, this inevitably means that simple indicators are chosen. As was noted earlier, such performance schemes are rarely effective. Policies to improve performance outcomes by targeting or rewarding only a few outputs have been frequently shown to have little to no observable effect on performance improvement or to undermine other policy objectives (Dougherty & Natow, 2015). What this paper demonstrates through its survey of productivity measurement, is that while the different approaches have strengths and weakness, taken together they make a case for employing more comprehensive measurement techniques as part of any allocation policies to enhance university performance.

Nonetheless, there remains the risk that for any productivity enhancing initiatives, the very act of measurement can influence the policies' effectiveness. Indicators and modelling are consequential, not just for the accuracy of measurement, but when they incentivise university leaders and managers to meet the metrics at the expense of other activities, undermining efforts to improve overall productivity. Despite the intuitive appeal of comprehensive measurement techniques to inform allocation, it may drive Goodhart's Law: 'once a measure becomes a target, it ceases to be a good measure' (Elton, 2004). This suggests there is a need to articulate assumptions and constraints of the techniques that both prudent government policy and university management might take into account. In this there is a role for further development of more sophisticated indicators available for measurement. While much has been progressed within the Australian context to implement new indicators, for instance, on educational quality and learning gain (Borden & Coates, 2017), there is further work to be done.

Rationally, governments should allocate funds based on available information, and so the transparency of any allocation policy to enhance performance becomes fundamental to its success. The transparency of the data and methods matters. This statement is non-trivial because any policy that seeks to utilise more sophisticated techniques of productivity measurement will likely use opaque assumptions and specifications. Even in a world with robust indicators, different parameterisations, weightings and estimations will yield varying results. For some this might be taken to affirm the futility or even irrelevance of empirical methods, but the inherent complexity itself is not an insurmountable barrier, so long as the allocation mechanisms and metrics informing them are transparent enough to be amenable to refinement. Together with greater transparency, there is a need for funding mechanisms that are flexible enough to evolve as higher education provision does. In such settings, productivity indicators which take account of resources, outcomes and intermediaries have an important and perhaps growing role to play.

It is important to assert, by way of conclusion, that the above analysis does not reinforce of promote scepticism or relativism. Students, government officials, university leaders and taxpayers have the right to ask whether the outcomes of higher education justify the costs of running the system. It is intuitive to want to link funding to performance, as may seem efficacious in other sectors and industries. In higher education, however, making progress likely hinges on laying better foundations as regards the measurement of productivity and how this informs policy settings.

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