Productivity Change in the Market Sectors of the Australian Economy

A Submission to the Productivity Commission Productivity Inquiry

by

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The Commission has been asked to review Australia's productivity performance and recommend a set of actionable policies that governments can use to increase productivity. To assist the Commission in its work, this submission (1) explains what most economists and statisticians mean by the term "productivity", (2) uses publicly-available Australian Bureau of Statistics (ABS) data to measure changes in productivity in sixteen market sectors of the Australian economy, (3) uses a combination of economic theory and statistical methods to estimate the drivers of productivity change in these sectors, (4) identifies government policies that can be used to target these different drivers, and (5) expresses a view on how governments should analyse productivity performance. In summary:

(1) Measures of productivity are defined as measures of output volume divided by measures of input volume. Common measures of productivity include measures of labour productivity (i.e., the volume of output divided by the volume of labour), multifactor productivity (i.e., the volume of output divided by the volume of some, but not all, factors of production) and total factor productivity (i.e., the volume of output divided by the volume of *all* factors of production).

(2) Most economists and statistical agencies measure productivity change in ways that are not consistent with the above definition. The measure of multifactor productivity (MFP) change routinely reported by the ABS, for example, simply cannot be viewed as a measure of output volume change divided by a measure of input volume change. The gaps between proper measures of productivity change (i.e., ones that are consistent with the above definition) and the ABS measure can be huge.

(3) If measures of productivity are measures of output volume divided by measures of input volume, then the factors that drive changes in productivity are the factors that drive changes in output and input volumes. Economists have many models that can be used to identify these factors. The models used in this submission indicate that the main drivers of productivity change in the Australian economy have been technical progress (i.e., the discovery of new techniques for transforming inputs into outputs), changes in technical efficiency (i.e., changes in how well existing technologies have been used) and economies and diseconomies of scale and substitution (i.e., changes in productivity associated with changing the scale of operations, the output mix and/or the input mix).

(4) If inputs of capital, energy, materials and services have any significant value, then governments should generally focus on increasing total factor productivity (TFP). They should bear in mind that (i) policies that target one driver of productivity change may have little or no effect on another driver, (ii) policies that lead to higher productivity in some sectors may lead to lower productivity in other sectors, and (iii) policies that target some drivers of productivity change may be totally ineffective.

(5) This submission recommends that governments: (i) define exactly what they mean by the term "productivity", (ii) compute measures of productivity change that are consistent with their definitions, (iii) use a combination of economic theory and statistical methods to explain variations in their measures, and (iv) use this information to develop evidence-based policies that target selected drivers of productivity change.

1. What is Productivity?

According to the OECD (2001, p.11) "[p]roductivity is commonly defined as a ratio of a volume measure of output to a volume measure of input use ... there is no disagreement on this general notion". Equivalent definitions can be found throughout the economics literature: see, for example, Jorgenson & Griliches (1967, p.249), Christensen & Jorgenson (1970, p.42), Chambers & Pope (1996, p.1140), O'Donnell (2018, p.2) and Sickles & Zelenyuk (2019, p.97). Importantly, measures of productivity are intrinsically different from measures of profitability (i.e., revenue divided by cost), profit (i.e., revenue minus cost), value-added (i.e., revenue minus the cost of intermediate inputs) and net output (i.e., output volume minus input volume).

Economists and statisticians like to distinguish between measures of partial, multifactor and total factor productivity. Measures of partial factor productivity (PFP) are measures of output volume divided by the volume of just one input (e.g., labour productivity is a measure of output volume divided by the volume of labour). Measures of multifactor productivity (MFP) are measures of output volume divided by the volume of some, but not all, inputs (usually capital and labour only). Measures of total factor productivity (TFP) are measures of output volume divided by the volume of all inputs. This submission has something to say about all these measures..

2. How Should Productivity Be Measured?

If measures of productivity are defined as measures of output volume divided by measures of input volume, then measuring changes in productivity involves measuring changes in volumes. Unfortunately, most economists and statisticians do this in ways that are not consistent with measurement theory.

Measurement theory is a branch of mathematics concerned with the assignment of numbers to objects. The basic principle underpinning measurement theory is trivially simple: when assigning numbers to bundles of inputs, for example, we must assign the so-called index numbers in such a way that the relationships between the numbers reflect the relationships between the bundles. To illustrate this basic principle, consider a sector that used the bundles of capital and labour inputs reported in Table 1. This table also reports two sets of volume index numbers: a set of geometric Young (GY) index numbers and a set of chained Törnqvist (CT) index numbers. Technical details concerning these indexes can be found in O'Donnell (2018, Ch. 3). Only the GY index numbers are consistent with measurement theory: observe, for example, that the GY index number in period 24 is only 0.74 times as big as the number in period 1, reflecting the fact that the sector used only 0.74 times as much capital and labour in period 24 as it did in period 1; also observe that the GY index number in period 25 is twice as large as the number in period 4, reflecting the fact that the sector used twice as much capital and labour in period 25 as it did in period 4. In contrast, the CT index numbers are complete rubbish: observe, for example, that the CT index number in period 11 is 2.596 times larger than the number in period 1, even though the same amount of capital and labour was used in both periods.

The GY index is a proper volume index in the sense that it satisfies the index number axioms listed in O'Donnell (2018, Ch. 3); relatedly, it also produces numbers that are consistent with measurement theory. The CT index is not a proper volume index and it does not yield numbers that are consistent with measurement theory. Surprisingly, the CT index is still being used by the ABS to measure changes in input volumes and, subsequently, produc-

[1] The numbers in this table come from rows 1, 4, 11, 24 and 25 of Tables 3.3 and 3.4 in O'Donnell (2018).

Table 1: Volume Index Numbers[1]

Period	Volume of Capital	Volume of Labour	GY Index	CT Index
1	1	1	1	1
4	1.05	0.7	0.831	0.774
11	1	1	1	2.596
24	0.74	0.74	0.74	2.068
25	2.1	1.4	1.662	4.724

tivity. The ABS makes an even more egregious error on the output side. By definition, the numerator in a productivity index should be a measure of output volume change. However, the numerator in the ABS MFP index is the change in real value-added.[2] This error does not cancel with the error made on the input side. Consequently, the ABS ends up producing a set of MFP index numbers that simply cannot be viewed as measures of output volume change divided by measures of input volume change (i.e., measures of productivity change).

It is natural to ask whether the errors made by the ABS are serious enough to make a difference to the productivity story. To find out, this submission uses publicly-available ABS data to compute four sets of productivity index numbers for each of sixteen sectors of the Australian economy for the period 1995–2019. The sixteen sectors are listed in Table 2. The four indexes are (i) a measure of labour productivity change (LPC), obtained by dividing an output volume index by a labour volume index, (ii) a proper measure of MFP change (MFPC), obtained by dividing an output volume index by a GY index measuring changes in capital and labour volumes, (iii) a proper measure of TFP change (TFPC), obtained by dividing an output volume index by a GY index measuring changes in all input volumes, and (iv) an ABS index (ABSI), obtained by dividing a real value-added index by a CT index that claims to measure changes in capital and labour volumes (the only difference between these ABSI numbers and the MFP index numbers published by the ABS is the choice of base period). Figure 1 presents the four sets of index numbers for each of Sectors A, B and D. Sets of index numbers for other sectors are presented in Appendix 1. The ABSI numbers in the top panel in Figure 1 would have us believe that MFP in the agriculture, forestry and fishing sector was 79% higher in 2019 than it was in 1995, whereas the proper measure of MFPC indicates that it was only 41% higher. Similarly, the ABSI numbers in the middle panel would have us believe that MFP in the mining sector was 23% lower in 2019 than it was in 1995, whereas the proper measure of MFPC indicates that it was 40% lower. Finally, it can

[2] Real value-added is deflated revenue minus the deflated cost of intermediate inputs. Under very restrictive assumptions, real value-added can be viewed as a measure of output volume minus the volume of intermediate inputs.

be seen from the bottom panel in Figure 1 that the ABSI numbers and the proper measure of MFPC both indicate that MFP in the electricity, gas, water and waste services sector was 24% lower in 2019 than it was in 1995. The bottom line is that the easily-avoidable errors made by the ABS are serious enough to make a difference to the productivity story in some, but not all, sectors.

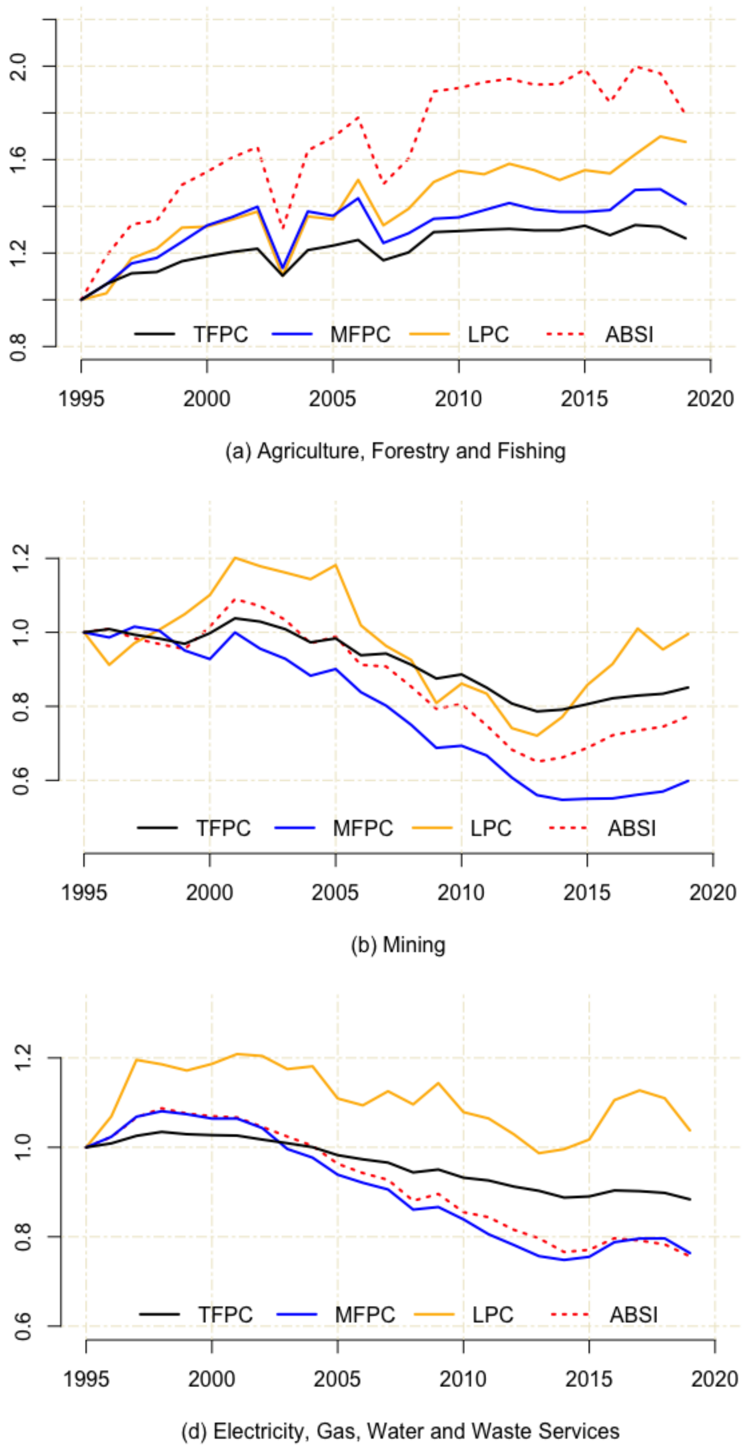
Table 2: Sectors

A	Agriculture, forestry and fishing
B	Mining
C	Manufacturing
D	Electricity, gas, water and waste services
E	Construction
F	Wholesale trade
G	Retail trade
H	Accommodation and food services
I	Transport, postal and warehousing
J	Information, media and telecommunications
K	Financial and insurance services
L	Rental, hiring and real estate services
M	Professional, scientific and technical services
N	Administrative and support services
R	Arts and recreation services
S	Other services

3. What are the Drivers of Productivity Change?

If measures of productivity are measures of output volume divided by measures of input volume, then the factors that drive changes in productivity are the factors that drive changes in output and input volumes. Economists have many models that can be used to identify these factors. The simplest of these models are production function models that express output volumes as functions of input volumes and characteristics of production environments. More sophisticated models also allow for technical progress and technical inefficiency. These more sophisticated models tell us that changes in output and input volumes, and therefore proper measures of productivity change, are driven by four main factors:

1. **Technical progress (TP)**: this refers to the discovery of new techniques, methods, systems and processes (i.e., new technologies) for transforming inputs into outputs (e.g., new hydroponic and vertical-farming techniques for growing crops; new autonomous navigation systems for transporting passengers and freight; new renewable power generation technologies).



(a) Agriculture, Forestry and Fishing

(b) Mining

(d) Electricity, Gas, Water and Waste Services

Figure 1: Measures of Productivity Change in Sectors A, B and D

2. **Environmental Change (EC)**: this refers to changes in variables that are physically involved in the production process but never controlled by managers (e.g., temperature and rainfall in agriculture; the road and rail networks in transport; temperature and topography in electricity distribution).

3. **Technical Efficiency Change (TEC)**: this refers to changes in how well managers make use of existing production technologies (e.g., choosing hydroponic crop-growing technologies over more conventional technologies, and implementing them well).

4. **Scale and Mix Efficiency Change (SMEC)**: this refers to changes in economies of scale and substitution. Economies of scale are the productivity gains associated with changing the scale of operations (e.g., increasing all inputs by x% in order to increase all outputs by more than x%). Economies of substitution are the productivity gains associated with changing the input mix and/or the output mix (e.g., substituting capital for labour, or producing less irrigated rice in order to produce more dryland maize).

In practice, estimating these different factors involves estimating changes in the limits to production (i.e., changes in production frontiers). Several so-called frontier estimators are available. The most common estimators are data envelopment analysis (DEA) and stochastic frontier analysis (SFA) estimators. DEA estimators are nonparametric estimators that can be used to decompose proper measures of productivity change into the product of the four factors listed above. Unfortunately, DEA estimators are underpinned by restrictive assumptions that are rarely, if ever, true: among other things, they assume that all inputs, outputs and environmental variables are observed and measured without error. SFA estimators are less restrictive because they allow for measurement errors and other sources of statistical noise. SFA estimators are parametric estimators that can be used to decompose proper measures of productivity change into the product of the four factors listed above, plus a fifth factor that measures **Changes in Statistical Noise (CSN)**.

To illustrate, this submission uses publicly-available data and SFA methods to estimate the main drivers of productivity change in each of the sixteen sectors of the Australian economy for the period 1995–2019. The types of inputs used in any given sector are generally quite different from the types of inputs used in any other sector (e.g., the tractors and other types of capital used in the agriculture sector are quite different from the rock drills and other types of capital used in the mining sector; and the types of labour used in the transportation sector are quite different from the types of labour used in the arts and recreation services sector). Production technologies and market outputs are also quite different from one sector to the next. For this reason, this submission uses SFA methods to estimate the parameters of sixteen separate stochastic production frontier models. Each model takes the following simple form:

$$
\begin{aligned}
\log(\text{market output}) = {} & \text{constant} + \text{trend1} + \text{trend2} + \text{trend3} \\
& + \log(\text{temperature}) + \log(\text{rainfall}) \\
& + \log(\text{capital}) + \log(\text{labour}) + \log(\text{other inputs}) \\
& - \log((\text{GHG emissions})/(\text{market output})) \\
& + \text{statistical noise} - \text{technical inefficiency}
\end{aligned}
$$

where the three trend terms are variables that allow rates of technical progress to vary across the three periods 1995–2004, 2005–2014 and 2015–2019 respectively. Data on temperature and rainfall were obtained from the Australian Bureau of Meteorology, and data on greenhouse gas (GHG) emissions were obtained from the Australian Department of Industry, Science, Energy and Resources. Bayesian methods were used to impose nonnegativity constraints on the coefficients of the trend terms and the log-inputs. Technical details concerning Bayesian estimation of stochastic production frontier models can be found in O'Donnell (2018, Sect. 8.4). Technical details concerning this particular empirical application (e.g., priors, length of MCMC chains etc.) are available on request. Table 3 presents coefficient estimates for Sectors A, B and D. Coefficient estimates for the remaining thirteen sectors are presented in Appendix 2.

Table 3: Coefficient Estimates for Sectors A, B and D

Variable	Agriculture etc. (a)	Mining (b)	Electricity etc. (d)
constant	−10.052	1.120	0.334
trend1	0.007	0.005	0.003
trend2	0.003	0.005	0.002
trend3	0.006	0.025	0.003
log(temperature)	0.248	0.262	−0.060
log(rainfall)	0.054	0.005	0.002
log(capital)	1.659	0.235	0.026
log(labour)	0.174	0.028	0.054
log(other inputs)	0.971	0.348	0.736
-log(GHG_emissions/market_outputs)	−0.088	0.060	−0.086

The coefficient estimates reported in Table 2 can be used to draw several conclusions about the drivers of productivity change. The estimates reported column (a), for example, indicate that, in the agriculture, forestry and fishing sector:

(i) technical progress in the period 1995–2004 (resp. 2015–2019) provided for a 0.7% (resp. 0.6%) per annum increase in the volume of output (and therefore all measures of productivity);

(ii) if all other variables (including sources of statistical noise) are held constant, then a one percent increase in temperature (resp. rainfall) will lead to a 0.248% (resp. 0.054%) increase in the volume of output (and therefore all measures of productivity);

(iii) if all other variables are held constant, then a one percent increase in the volume of capital will lead to a 1.659% (resp. 0.971%) increase in the volume of output (and therefore labour productivity);

(iv) if all other variables are held constant, then a one percent increase in the volume of other inputs will lead to a 0.971% increase the volume of output (and therefore labour productivity and MFP).

The coefficient estimates reported in columns (b) and (d) (and in Appendix 2) can be used to draw similar conclusions about the drivers of productivity change in Sectors B and D (and the remaining thirteen sectors). What they don't immediately tell us is exactly what drove productivity change over the period 1995–2019.

O'Donnell (2018, Sect. 8.5.2) explains how the estimated parameters of stochastic frontier models can be used to explain variations in proper measures of productivity change. This submission has used the O'Donnell methodology to decompose the measures of TFP change (TFPC) depicted earlier in Figure 1. The results are presented in Figure 2. Results for other sectors are presented in Appendix 3. The top panel in Figure 2 indicates that TFP in the agriculture, forestry and fishing sector was 26.3% higher in 2019 than it had been in 1995. The breakdown of this increase is as follows:

$$\begin{aligned} \text{TFPC} &= \text{TP} \times \text{EC} \times \text{TEC} \times \text{SMEC} \times \text{CSN} \\ &= 1.124 \times 0.981 \times 1.055 \times 1.083 \times 1.003 = 1.263. \end{aligned}$$

This decomposition indicates that between 1995 and 2019, technical progress contributed to a 12.4% increase in TFP, a deterioration in the production environment led to a $(1-0.981) =$ 1.9% fall in TFP, increases in technical efficiency contributed to a 5.5% increase in TFP, increases in scale and mix efficiency contributed to an 8.3% increase in TFP, and changes in various sources of statistical noise accounted for a mere 0.03% increase in measured TFP. Results for intervening years suggest that the main long-term driver of TFPC in the agriculture, forestry and fishing sector has been technical progress, and the main short-to-medium-term drivers have been changes in technical, scale and mix efficiency. The productivity stories in the other sectors are quite different. The middle (resp. bottom) panel in Figure 2 indicates that TFP in the mining (resp. electricity, gas, water and waste services) sector was 14.9% (resp. 11.6%) lower in 2019 than it had been in 1995. In both cases, the productivity gains associated with technical progress were more than offset by very large falls in scale and mix efficiency. More will be said about this below.

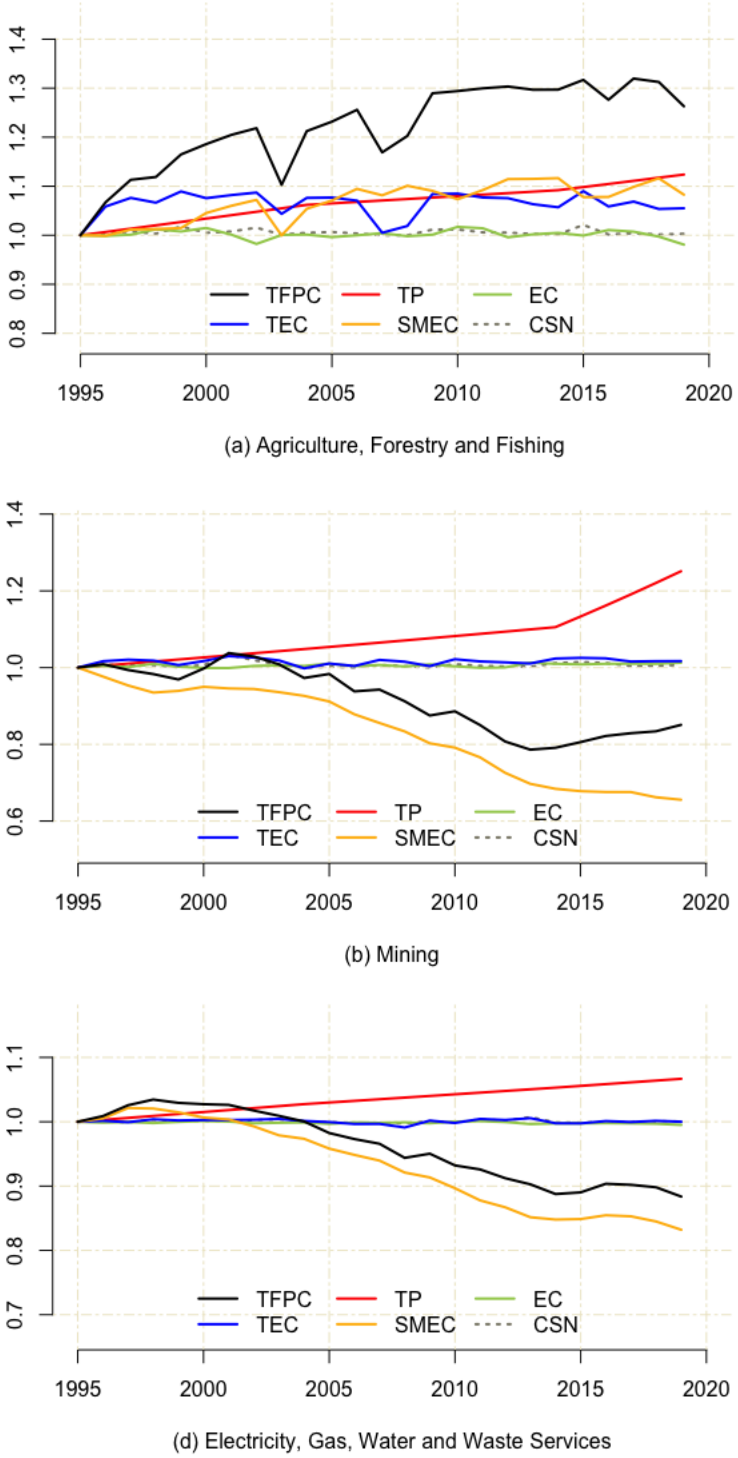


Figure 2: The Drivers of TFP Change in Sectors A, B and D

4. How Can Governments Increase Productivity?

If governments are interested in increasing productivity, then there are several things to bear in mind. First, unless inputs of capital, energy, materials and services are worthless, then any interest in labour productivity is misplaced. As Farrell (1957) puts it, "[i]gnoring as it does all inputs save labour, [labour productivity] is so obviously unsatisfactory [as a measure of economic performance] that one would not waste space discussing it, were it not for the danger that its popularity with the general public may do the economy serious harm through over-capitalization. Very often, the easiest way to increase the average productivity of labour in an industry is to use more machinery" (p. 26). In the case of Australian agriculture, for example, a one percent increase in the volume of capital is estimated to increase labour productivity by 1.659% (see Section 3). If inputs of capital, energy, materials and services are of some value, then they must be taken into account when measuring economic performance. This suggests that governments should generally focus on TFP.

Second, increases in productivity are sometimes associated with lower profits. Conversely, decreases in productivity are sometimes associated with higher profits. This was, in fact, the experience of the Australian mining sector between 2002 and 2013. In that period, a significant improvement in the terms-of-trade incentivised large profit-maximising mining companies to expand their operations to the point where they encountered significant diseconomies of scale. This resulted in a significant decrease in scale and mix efficiency and an associated fall in TFP (see the middle panel in Figure 2). At the same time, the improvement in the terms-of-trade resulted in substantial increases in profits. Policy-makers with a limited understanding of the drivers of productivity change dubbed the fall in productivity a paradox. In fact, it created such widespread consternation amongst policy-makers and politicians that the Australian government launched a landmark Parliamentary Inquiry aimed at identifying the underlying causes of the paradox. They presumably hoped to implement policies that could reverse the productivity slump. Given that the falls in productivity were associated with increases in profits, we can only imagine that mining companies would have been rather unhappy about any policies that turned the clock back.

Third, as the above example illustrates, good government policy-making requires a good theoretical understanding of the economic drivers of productivity change. Economists have many models that can be used to identify these drivers. Unfortunately, some of the most widely-used models are underpinned by assumptions that are rarely, if ever, true. Growth accounting models, for example, are underpinned by the assumption that production frontiers exhibit constant returns to scale; this is rarely true, and it rules out the scale efficiency component of productivity change. Growth accounting models also assume that firms are price-takers in input markets and managers successfully minimise costs; this is also rarely true, and it rules out the technical efficiency component of productivity change. Scale efficiency change and technical efficiency change are important drivers of productivity change in several sectors of the Australian economy. For more details on growth accounting models (and the reasons why the assumptions underpinning these models are rarely, if ever, true), see O'Donnell (2018, Set. 7.2).

Fourth, different government policies potentially effect, and can therefore be used to target, the different drivers of productivity change. The main drivers are:

1. **Technical progress (TP)**: this refers to the discovery of new production techniques. Investigative activities aimed at discovering new production techniques are known as research and development (R&D) activities. Governments may be able to increase the rate of technical progress by, for example: providing more R&D funds to government agencies (e.g., the CSIRO); increasing the amount of research funding available to universities and other organisations that conduct research (e.g., through the ARC); amending intellectual property rights legislation to incentivise individuals and organisations to conduct more R&D (e.g., by extending the maximum periods during which patents and other intellectual property claims can be enforced under the TRIPs agreement).

2. **Environmental Change (EC)**: this refers to changes in variables that are physically involved in the production process but beyond the control of managers. Governments can help maintain or improve production environments by, for example, regulating the impact of economic activities on the natural environment (e.g., regulating GHG emissions to help control long-term changes in temperature and rainfall) and by providing more and better public infrastructure (e.g., roads, ports, electricity infrastructure, grain storage facilities).

3. **Technical Efficiency Change (TEC)**: this refers to how well firm managers make use of existing production techniques (i.e., how well they choose a technique, and how well they implement it). Governments can increase levels of technical efficiency by, for example, removing barriers to the adoption of particular techniques (e.g., removing patent protections; removing financial constraints that prevent the purchase of necessary inputs), and by providing education and training services to advise managers on the existence and proper implementation of new techniques (e.g., agricultural extension programs).

4. **Scale and Mix Efficiency Change (SMEC)**: this refers to the potential benefits associated with changing the scale of operations, the output mix and/or the input mix. Governments can influence levels of scale and mix efficiency by changing the variables that drive managerial behaviour. If, for example, firms are price takers in input markets and they minimise costs, then changes in the relative prices of capital and labour will induce managers to change the capital to labour ratio (i.e., the input mix).

Indeed, in many industries, often the easiest way for governments to change levels of scale and mix efficiency is by changing relative output and input prices (e.g., by changing interest rates, wage rates, taxes and subsidies). It is also possible for governments to change levels of scale and mix efficiency by placing, or removing, legal restrictions on output and input choices (e.g., prohibiting the use of child labour; banning exports or imports of certain goods; regulating the production of genetically-modified crops).

A few other things to bear in mind are that (i) policies that target one component of productivity change may have little or no effect on another component (e.g., policies that target the technical progress component may have little effect on the environmental change component, even in the long term), (ii) policies that lead to higher productivity in some sectors may lead to lower productivity in other sectors (e.g., lowering interest rates will likely increase productivity in sectors that are under-capitalised and lower productivity in sectors that are over-capitalised), and (iii) policies that target some components of productivity change may be totally ineffective (e.g., education and training policies aimed at improving levels of technical efficiency will be totally ineffective if firms are already operating on the production frontier).

5. Recommendations

This submission recommends that governments:

(i) define exactly what they mean by the term ”productivity”,

(ii) compute measures of productivity change that are consistent with their definitions,

(iii) use a combination of economic theory and statistical methods to explain variations in their measures, and

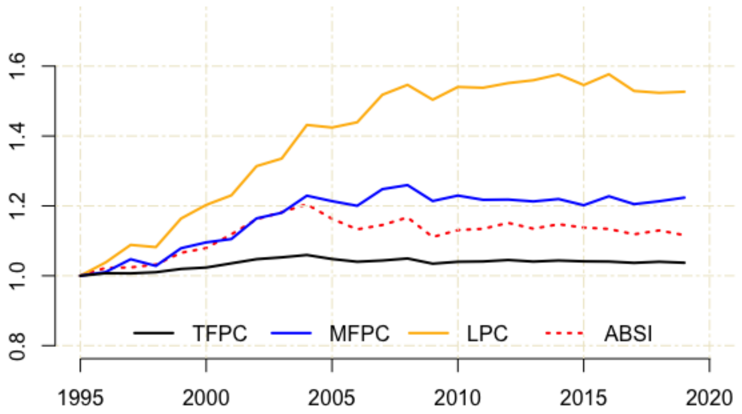
(iv) use this information to develop evidence-based policies that target selected drivers of productivity change.

This submission demonstrates how easily these things can be done. As a final comment, it would not be unreasonable for the Commission to ask why statistical agencies continue to compute volume index numbers in nonsensical ways (e.g., using the CT index). Most economists fall back on claims made by the well-known American economist, Irving Fisher. The scientific basis for Fisher's claims is unclear; Samuelson & Swamy (1974, p.575) put his main claim down to hubris. Fisher, incidentally, is also known for making possibly the worst economic prediction in history: on the eve of the 1929 Wall Street crash, he wrote that "Stock prices have reached what looks like a permanently high plateau". Another possible reason for computing volume index numbers in nonsensical ways is bureaucratic inertia (i.e., the tendency for large organisations to continue using established computational practices even when they are known to be flawed). This must change.

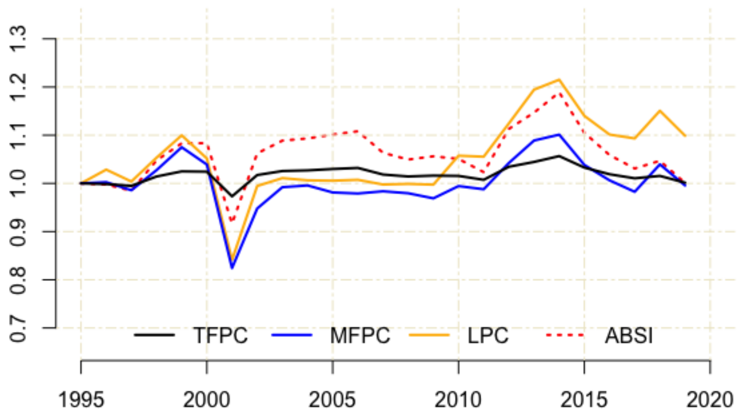
Appendix 1: Measures of Productivity Change

The data used to prepare the following figures can be obtained from the author on request (send an email to c.odonnell@economics.uq.edu.au). The acronyms used in the figures are as follows:

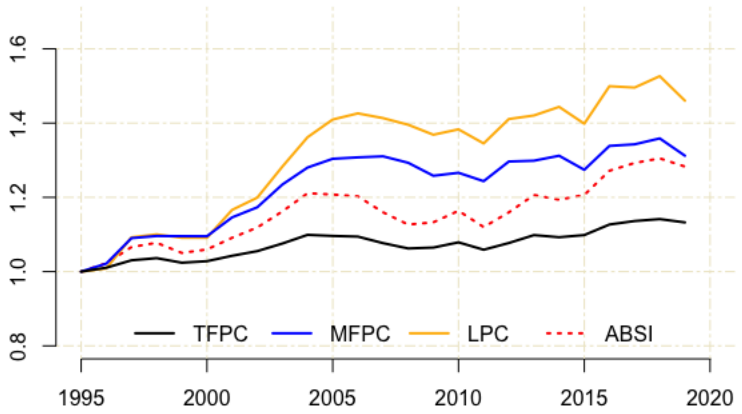
TFPC = total factor productivity change
MFPC = multifactor productivity change
LPC = labour productivity change
ABSI = Australian Bureau of Statistics index



(c) Manufacturing

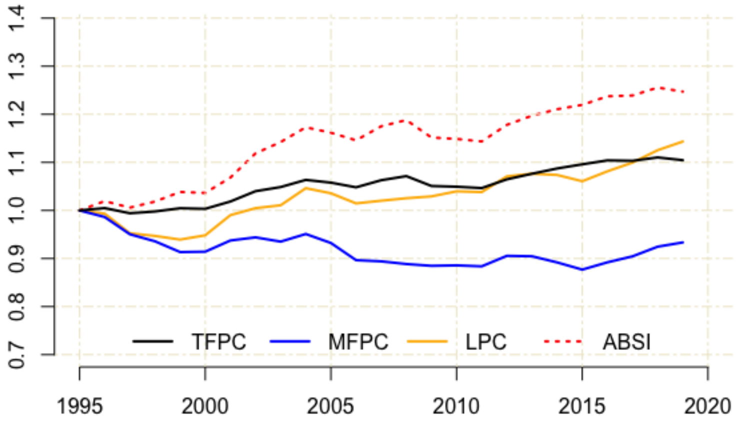


(e) Construction

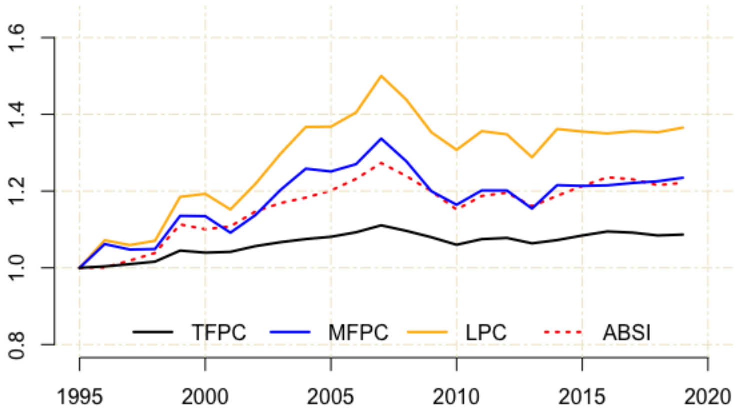


(f) Wholesale Trade

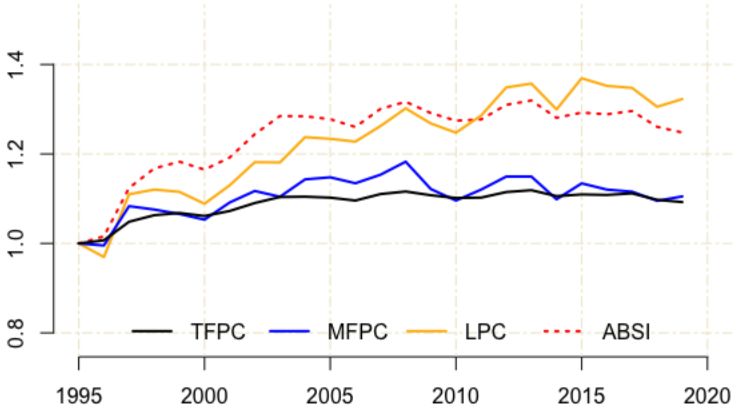
Figure 3: Measures of Productivity Change in Sectors C, E and F



(g) Retail Trade

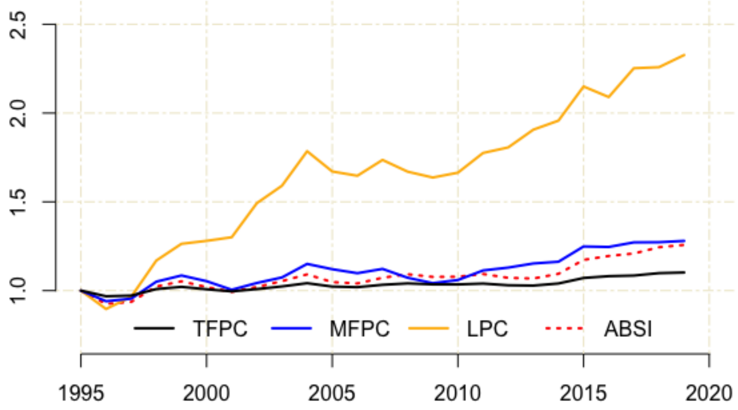


(h) Accommodation and Food Services

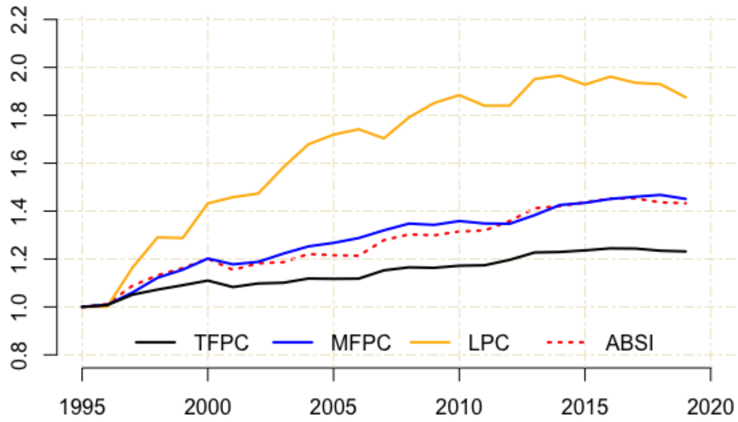


(i) Transport, Postal and Warehousing

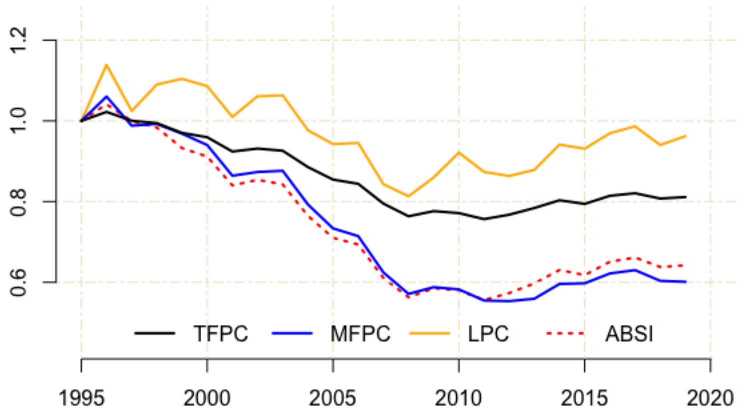
Figure 4: Measures of Productivity Change in Sectors G, H and I



(j) Information, Media and Telecommunications

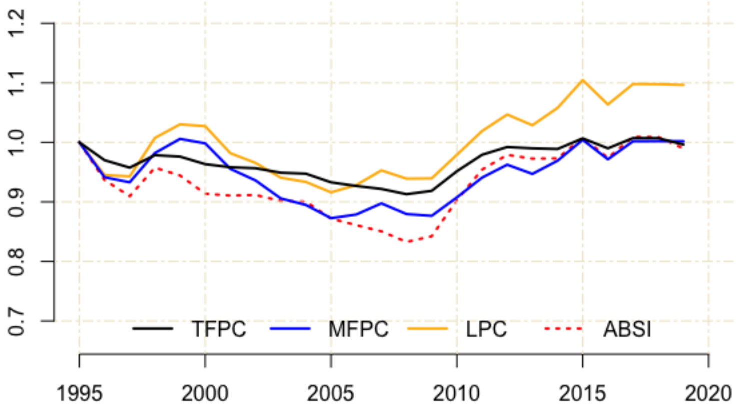


(k) Financial and Insurance Services

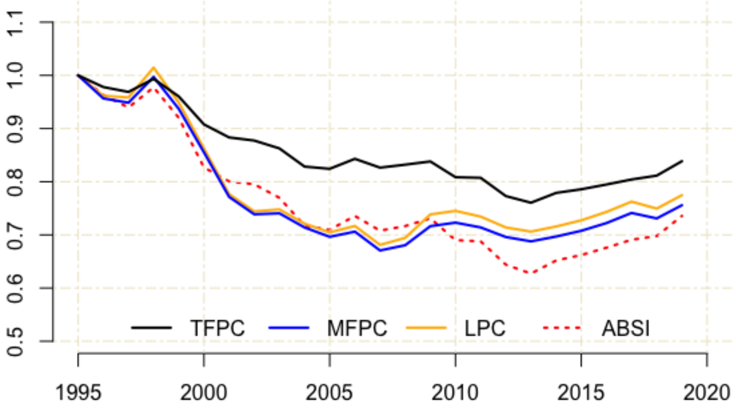


(l) Rental, Hiring and Real Estate Services

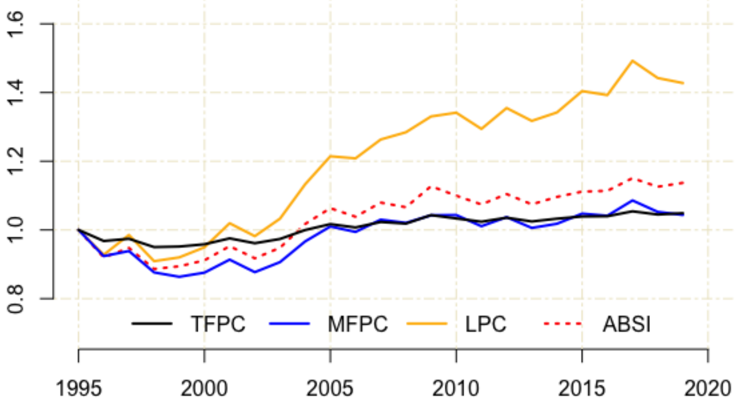
Figure 5: Measures of Productivity Change in Sectors J, K and L



(m) Professional, Scientific and Technical Services



(n) Administrative and Support Services



(r) Arts and Recreation Services

Figure 6: Measures of Productivity Change in Sectors M, N and R

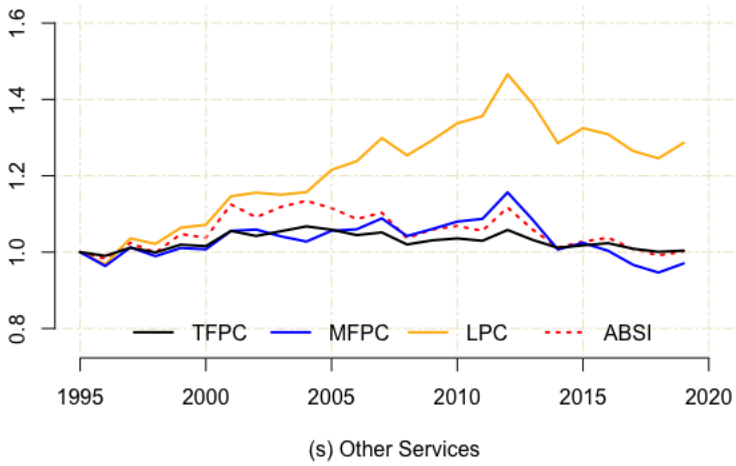


Figure 7: Measures of Productivity Change in Sector S

Appendix 2: Coefficient Estimates

Table 4: Coefficient Estimates for Sectors C, E and F

Variable	Manufacturing (c)	Construction (e)	Wholesale Trade (f)
constant	1.190	0.857	−0.693
trend1	0.008	0.009	0.015
trend2	0.001	0.003	0.005
trend3	0.001	0.002	0.009
log(temperature)	−0.328	0.060	0.500
log(rainfall)	−0.021	0.002	0.025
log(capital)	0.035	0.025	0.327
log(labour)	0.096	0.051	0.159
log(other inputs)	0.713	0.760	0.324
-log(GHG_emissions/market_outputs)	−0.094	0.086	0.118

Table 5: Coefficient Estimates for Sectors G, H and I

Variable	Retail Trade (g)	Accommodation & Food Services (h)	Transport, Postal, etc. (i)
constant	2.165	0.894	−0.121
trend1	0.012	0.008	0.012
trend2	0.010	0.001	0.005
trend3	0.009	0.008	0.002
log(temperature)	−0.100	−0.082	0.176
log(rainfall)	−0.026	0.003	0.014
log(capital)	0.171	0.097	0.059
log(labour)	0.201	0.087	0.055
log(other inputs)	0.274	0.653	0.708
-log(GHG_emissions/market_outputs)	0.102	−0.004	−0.027

Table 6: Coefficient Estimates for Sectors J, K and L

Variable	Information, Media etc. (j)	Financial & Insurance etc. (k)	Rental, Hiring etc. (l)
constant	1.807	−0.259	0.267
trend1	0.016	0.015	0.003
trend2	0.008	0.011	0.011
trend3	0.022	0.006	0.006
log(temperature)	−0.316	0.111	0.202
log(rainfall)	0.007	0.037	−0.022
log(capital)	0.104	0.308	0.020
log(labour)	0.067	0.186	0.032
log(other inputs)	0.568	0.384	0.799
-log(GHG_emissions/market_outputs)	−0.003	0.004	0.146

Table 7: Coefficient Estimates for Sectors M, N and R

Variable	Professional, Scientific etc. (m)	Administrative & Support Services (n)	Arts and Rec. Services (r)
constant	1.828	3.492	−0.636
trend1	0.008	0.006	0.003
trend2	0.012	0.005	0.002
trend3	0.009	0.024	0.002
log(temperature)	−0.121	−0.559	0.184
log(rainfall)	−0.011	−0.007	0.009
log(capital)	0.054	0.111	0.036
log(labour)	0.090	0.262	0.059
log(other inputs)	0.573	0.220	0.892
-log(GHG_emissions/market_outputs)	0.140	0.009	–

Table 8: Coefficient Estimates for Sector S

Variable	Other Services (cs)
constant	2.474
trend1	0.013
trend2	0.004
trend3	0.006
log(temperature)	-0.265
log(rainfall)	-0.012
log(capital)	0.033
log(labour)	0.165
log(other inputs)	0.448
-log(GHG_emissions/market_outputs)	0.061

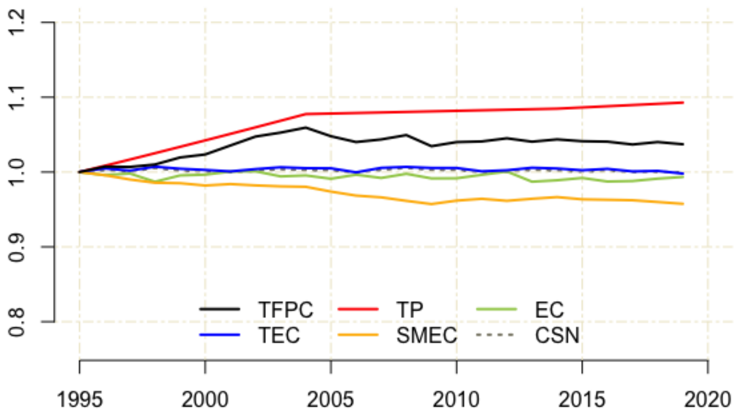
Appendix 3: The Drivers of TFP Change

The data used to prepare the following figures can be obtained from the author on request (send an email to c.odonnell@economics.uq.edu.au). The acronyms used in the figures are as follows:

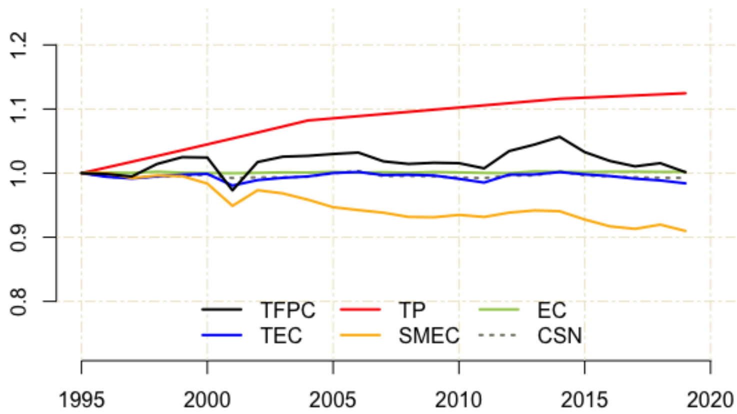
TFPC = total factor productivity change
TP = technical progress
EC = environmental change
TEC = technical efficiency change
SMEC = scale and mix efficiency change
CSN = change in statistical noise

Note that:

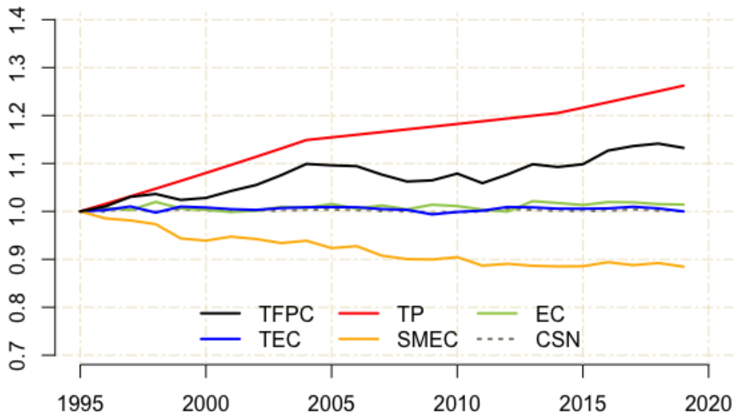
$$\text{TFPC} = \text{TP} \times \text{EC} \times \text{TEC} \times \text{SMEC} \times \text{CSN}.$$



(c) Manufacturing

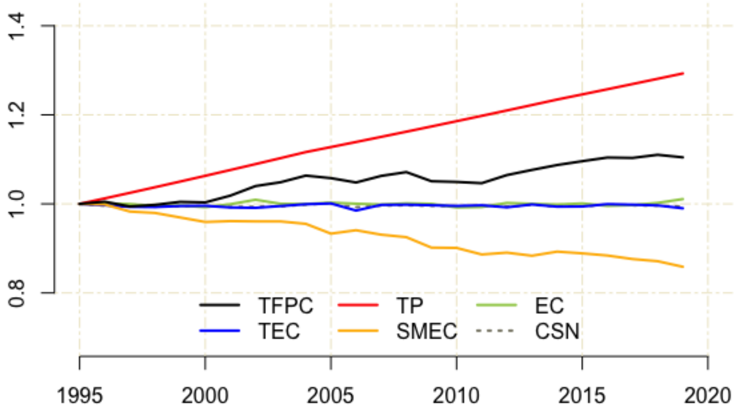


(e) Construction

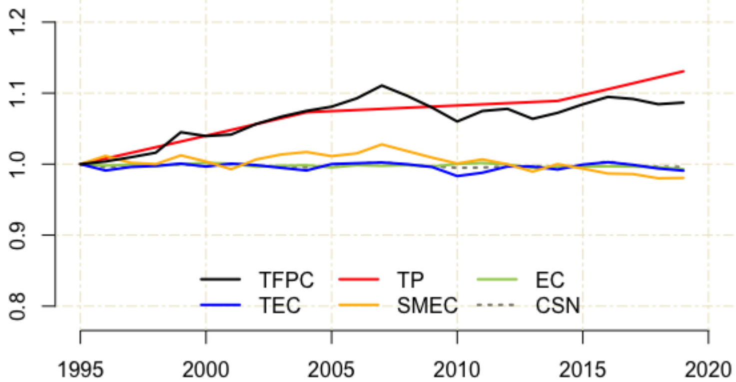


(f) Wholesale Trade

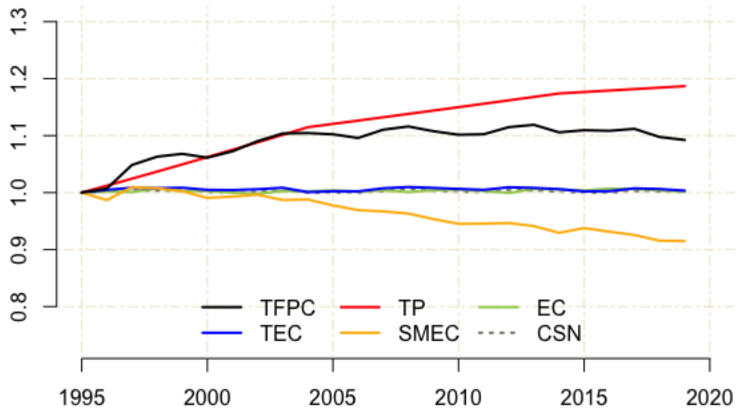
Figure 8: The Drivers of TFP Change in Sectors C, E and F



(g) Retail Trade

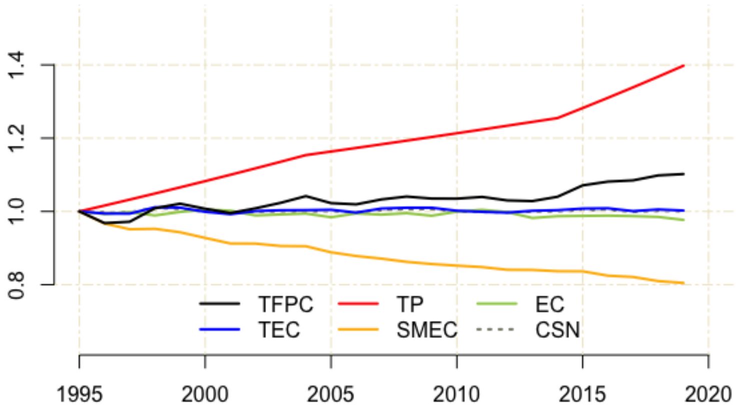


(h) Accommodation and Food Services

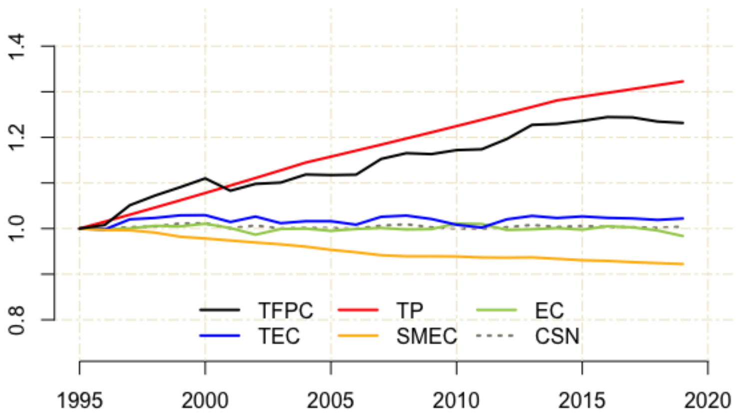


(i) Transport, Postal and Warehousing

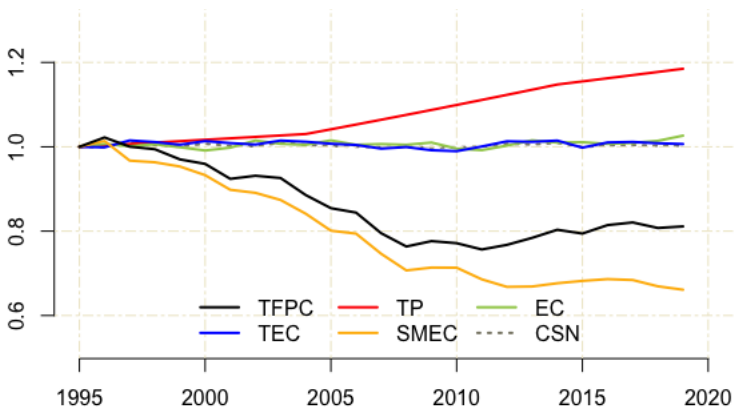
Figure 9: The Drivers of TFP Change in Sectors G, H and I



(j) Information, Media and Telecommunications

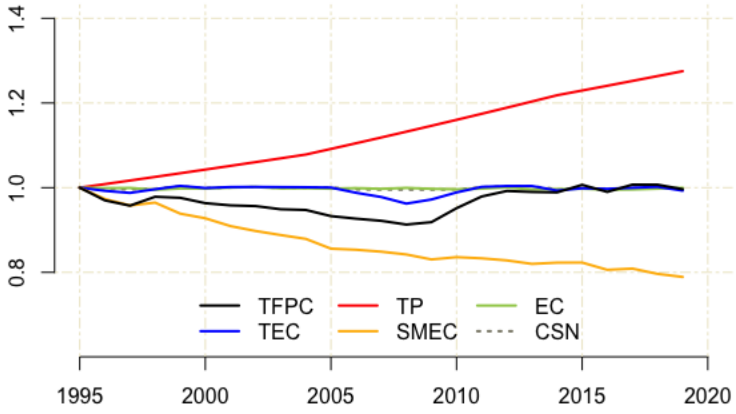


(k) Financial and Insurance Services

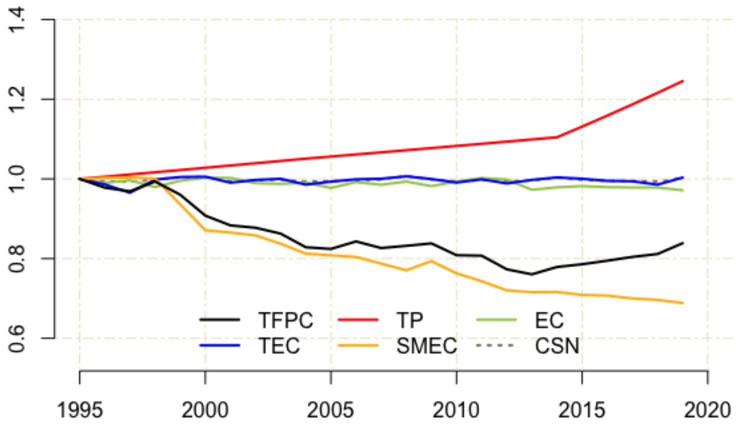


(l) Rental, Hiring and Real Estate Services

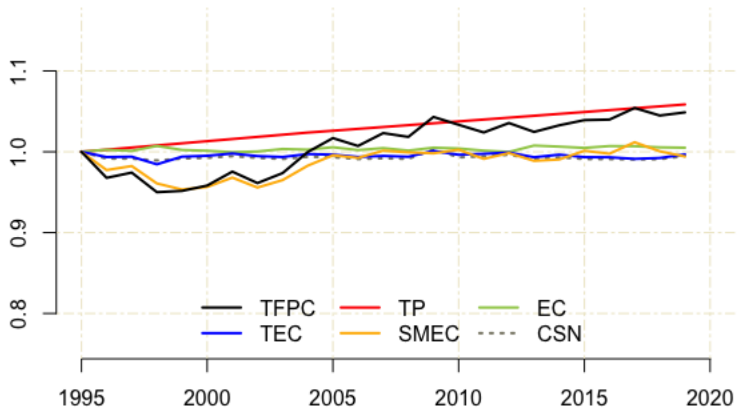
Figure 10: The Drivers of TFP Change in Sectors J, K and L



(m) Professional, Scientific and Technical Services



(n) Administrative and Support Services



(r) Arts and Recreation Services

Figure 11: The Drivers of TFP Change in Sectors M, N and R

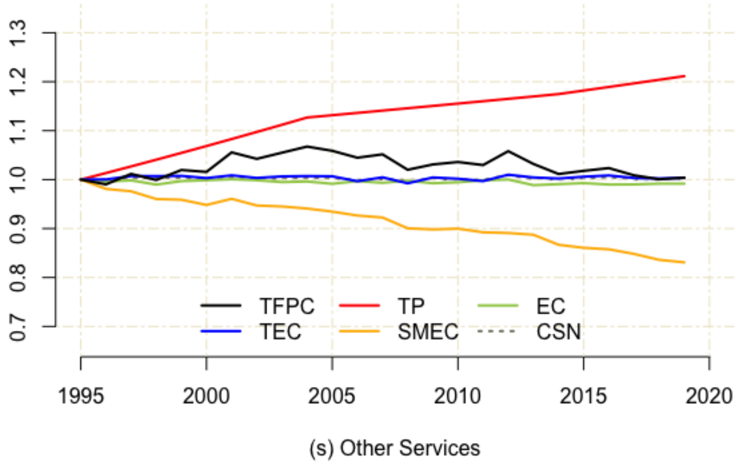


Figure 12: The Drivers of TFP Change in Sector S

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