

Productivity differentials for valuation of move to more (or less) productive jobs

Praveen Thakur¹, Lulu Zeng¹, Thao-Mi Bui¹

¹KPMG

Email for correspondence: lzeng3@kpmg.com.au

1. Introduction

Major transport infrastructure investments that enhance connectivity and reduce travel times can spur employees to change jobs – by changing the location and/or industry of their work. This can improve their productivity where there are ‘place-based’, labour productivity differences between locations. For example, an investment banker currently working in the suburbs but who changes jobs to work in the Central Business District (CBD) may experience an uplift in their labour productivity due to being closer to a denser network of potential clients and colleagues who can share their knowledge. The increase in labour productivity - as reflected by a higher wage - results in an increase in income tax revenue. This benefit can be captured in cost-benefit analysis.

Economic appraisal of transport projects in Australia has long sought to capture the place-based productivity benefits of a move to more (or less) productive jobs (M2MLPJ) (also referred to as Wider Economic Benefit 2b (WEB2b)). The Australian Transport Assessment and Planning (ATAP) guidelines previously used the average wage of a location to proxy for the productivity of its place-based attributes. However, this is no longer officially recognized as it introduces a significant bias given that the wage that an employee earns in a given location captures more than the location’s place-based attributes – it reflects their skill set and experience as well as the characteristics of the firm for which they work. ATAP guidelines now suggest that if productivity differentials that reflect only the place-based attributes of each location are provided, then the benefit of the movement of jobs to different locations can be quantified as part of cost-benefit analysis. To date, lack of availability of such productivity differentials in Australia have prevented the robust quantification of M2MLPJ.

This paper provides such productivity differentials by small areas across Greater Melbourne. These productivity differentials provide a high level of spatial resolution as well as accounting for industrial differences in place-based productivity, a dimension that has not been provided previously in any transport economic appraisal guidance. Their use will be demonstrated in a case study using a high-profile transport infrastructure project in Greater Melbourne. This paper finds that productivity differentials that remove the impact of employee and firm characteristics reveal greater spatial variation in place-based productivity across Greater Melbourne. Current practices that apply average wage by location inflate the benefits of relocation of jobs towards dominant city centres. The use of these place-based productivity differentials is an important step in more accurately reflecting the benefits of transport infrastructure investments that improve connections beyond dominant, monocentric city centres.

Importantly, the productivity differentials estimated by this paper can be used to quantify M2MLPJ in a robust manner that meets ATAP requirements. The methodology used here can

also be replicated to produce productivity differentials for other jurisdictions where estimates are unavailable.

2. Data

Panel data was effectively constructed using SA2s by industry as ‘individuals’. These were pooled across 2011 and 2016 using Census data from the Australian Bureau of Statistics (ABS) in order to obtain a sufficient sample size to estimate productivity differentials by SA2. The use of SA2s enable estimation of productivity differentials at a sufficiently disaggregated level whilst retaining a sufficient number of individuals in a given small area and industry to produce a reliable constructs of the variables required. Weighted average wage, levels of education and hours worked were constructed for each SA2 and industry using counts of those employed in a given SA2 and industry. The construction and choice of these variables is outlined further in Section 3 with the model specification.

Observations for SA2s and industries that had an employment density below the 35th percentile for a given industry were removed. These SA2s and industries had insufficient individuals to construct reliable values for the variables required; as such, these observations only contribute to model noise and not adding meaningful explanatory power to the model. The removal of these observations does not affect model fit. This was done by industry to account for differences in employment density by industry. For example, agricultural industries are typically less employment dense than professional services. The threshold for removal of observations was chosen to maintain as much of the sample as possible, with the bare minimum employment numbers to obtain robust estimates. **Table 1** shows the average and minimum employment densities by industry after the removal of observations:

Table 1: Summary of employment density (Employed persons per sq.km) after removal of observations

Industry	Average employment density after observation removal	Minimum employment density after observation removal
Agriculture, Forestry and Fishing	3.8	0.4
Mining	5.1	0.01
Electricity, Gas, Water and Waste Services	20.8	0.1
Rental, Hiring and Real Estate Services	27.8	0.7
Arts and Recreation Services	37.3	0.8
Wholesale Trade	41.4	1
Other Services	48.1	2.4
Information Media and Telecommunications	52.6	0.4
Administrative and Support Services	52.8	1.7
Transport, Postal and Warehousing	56.9	2
Construction	72.7	6.7
Manufacturing	73.4	2.2
Public Administration and Safety	96.4	1.6
Accommodation and Food Services	107.4	4.3
Financial and Insurance Services	115.4	0.8
Education and Training	119.6	5.4
Retail Trade	131.7	6.3
Health Care and Social Assistance	175.4	7.1
Professional, Scientific and Technical Services	192.9	2.6

3. Methodology

This paper leverages the theoretical basis from Johnson et al. (2008), which demonstrated that total labour productivity, as measured by wage, reflects employee and firm characteristics and locational advantages. This methodology forms the basis of the UK’s Transport Analysis Guidance (TAG) methodology for quantification of M2MLPJ.

This paper constructs a dataset and adopts a model specification that addresses critiques of current leading practice of the quantification of M2MLPJ by the UK TAG. The review of this practice by Laird et al. (2019) for the UK’s Department of Transport noted two key critiques – that productivity differentials should be estimated at a sufficiently high level of spatial resolution as well as consider industrial differences in place-based productivity. The chosen econometric model specification for this study corrects the issues of the UK TAG model, and is given as follows with variables defined in **Table 2**:

$$\log(wage_{i,l}) = \beta_0 + \beta_1 Age_{i,l} + \beta_2 Hours\ Worked_{i,l} + \beta_3 Education_{i,l} + \alpha^{Loc} Location_{i,l} + \alpha^{Ind} Industry_{i,l} + \alpha^{LocInd} Location_{i,l} \times Industry_{i,l} + \epsilon_{i,l}$$

where:

- i = 1, ..., N SA2s (the omitted reference SA2 is ‘Melbourne’, which is centred on Melbourne CBD)
- l = 1, ..., 18 industries (19 industries as defined by ANZSIC codes, the omitted reference industry is M – Professional, Scientific and Technical Services)¹

Table 2: Model variables

Variable	Definition
Wage_{i,l}	Weighted average weekly wage (inflation adjusted) of workers for each SA2/industry
Age_{i,l}	Weighted average age of workers for each SA2 and industry
Hours Worked_{i,l}	Weighted average weekly hours worked of workers for each SA2 and industry
Education_{i,l}	Proportion of workers in that SA2 and industry with education beyond secondary school

Source: ABS (2016, 2011), *Census - Place of Work*

Several alternative control variables were trialled. In particular, the occupation of individuals and their gender. The variables chosen produced good model fit, results that validated best, a parsimonious model, and minimised multicollinearity issues. No explicit controls for firm characteristics were used due to:

- **Unavailability of controls for firm characteristics in the Victorian and Australian context.** The key potential source of firm data at a reasonable level of geographical disaggregation is the ABS Counts of Australian Businesses (2011, 2016), Cat. 8165. However, it counts businesses by Australian Business Number, reflecting the location of the head office rather than the firm’s operations.
- **Self-selection of employees into more productive firms.** As a result, firm characteristics are likely to be at least partially captured by our controls for employee characteristics. (Correlation between the education variable and weighted average annual turnover is approximately -0.1).

Place-based productivity differentials are constructed for each SA2 and industry pair with reference to the omitted reference SA2 and industry (which is set to 1) using the relevant estimated coefficients from $\hat{\alpha}^{Loc}$, $\hat{\alpha}^{Ind}$ and $\hat{\alpha}^{LocInd}$.² Areas that were not estimated in the regression model were assigned the minimum productivity differential for that particular industry, given these areas had significantly lower employment density and are expected to be less productive. Other methods to assign averages and neighbouring values to areas without

¹ This omitted reference is chosen simply for ease of interpretation.

² Percentage calculation is obtained using the standard formula: $(e^{\hat{\alpha}} - 1)$.

estimates were explored but were susceptible to producing overinflated values given the low employment in these areas.

Given estimates of the net change in jobs in a given SA2 and industry,³ the annual benefit of M2MLPJ can then be quantified as follows:

$$M2MLPJ = \sum_m \sum_i (\Delta Jobs_{i,m} \times PD_{i,m} \times Average Annual Wage (pre - tax) \times Tax rate)$$

where:

- i = 1,...,N SA2s
- m = 1,...,19 industries
- PD = Estimated productivity differential

4. Key results and discussion

The estimated model coefficients for the main effects are given in **Table 3**. The coefficients reflect the expected direction and the adjusted R² demonstrates good model fit. The degrees of freedom is sufficiently high to support the large number of fixed effect coefficients estimated.

Table 3: Estimated model coefficients

Variable	Coefficient estimate
(Intercept)	6.5891***
Age _{i,l}	0.0051***
Hours Worked _{i,l}	0.0036***
Education _{i,l}	0.5657***
Adj R ² = 0.79	
Obs: 8,379	
Degrees of freedom: 3,765	

*** Significant at 5% level

As seen in **Figure 1**, clustering of the fitted and actual wage around the 45 degree line of perfect fit shows the model is well fitted across industries. **Figure 2** provides an example of the estimated place-based productivity differentials for the industry of ‘Transport, Postal and Warehousing’ and compares them with wage differentials. This highlights the key practical difference between the use of wage differentials and place-based productivity differentials. The wage differentials on the left suggest that if individuals take jobs outside of Melbourne CBD, they will experience a uniform decrease in their productivity. The place-based productivity differentials on the right show that whilst areas outside of inner Melbourne have lower place-based productivity, the difference is not as stark as that suggested by the wage differentials. Once employee and firm characteristics have been controlled for, areas that are expected to have relatively greater productivity such as the Western State Significant Industrial Precinct, the northern Meat Markets and the south-eastern industrial areas down towards Dandenong are shown to be closer in place-based productivity compared to the SA2 of Melbourne CBD. The use of these place-based productivity differentials will therefore more accurately capture the variation in place-based productivity across Greater Melbourne than the wage differentials. Average productivity differentials are summarized by key SA4s and industries in **Table 4** of the **Appendix** for further detail.

³ KPMG uses CityPlan and the Victorian Integrated Transport Model as a Land Use and Transport Interaction model.

Statistical diagnostic checks have been undertaken to ensure model validity and robustness, these include tests for multicollinearity, homoskedasticity, spatial dependence and data distribution normality.

Figure 1: Fitted versus actual plots by industry (y axis = productivity differential, x axis = wage)

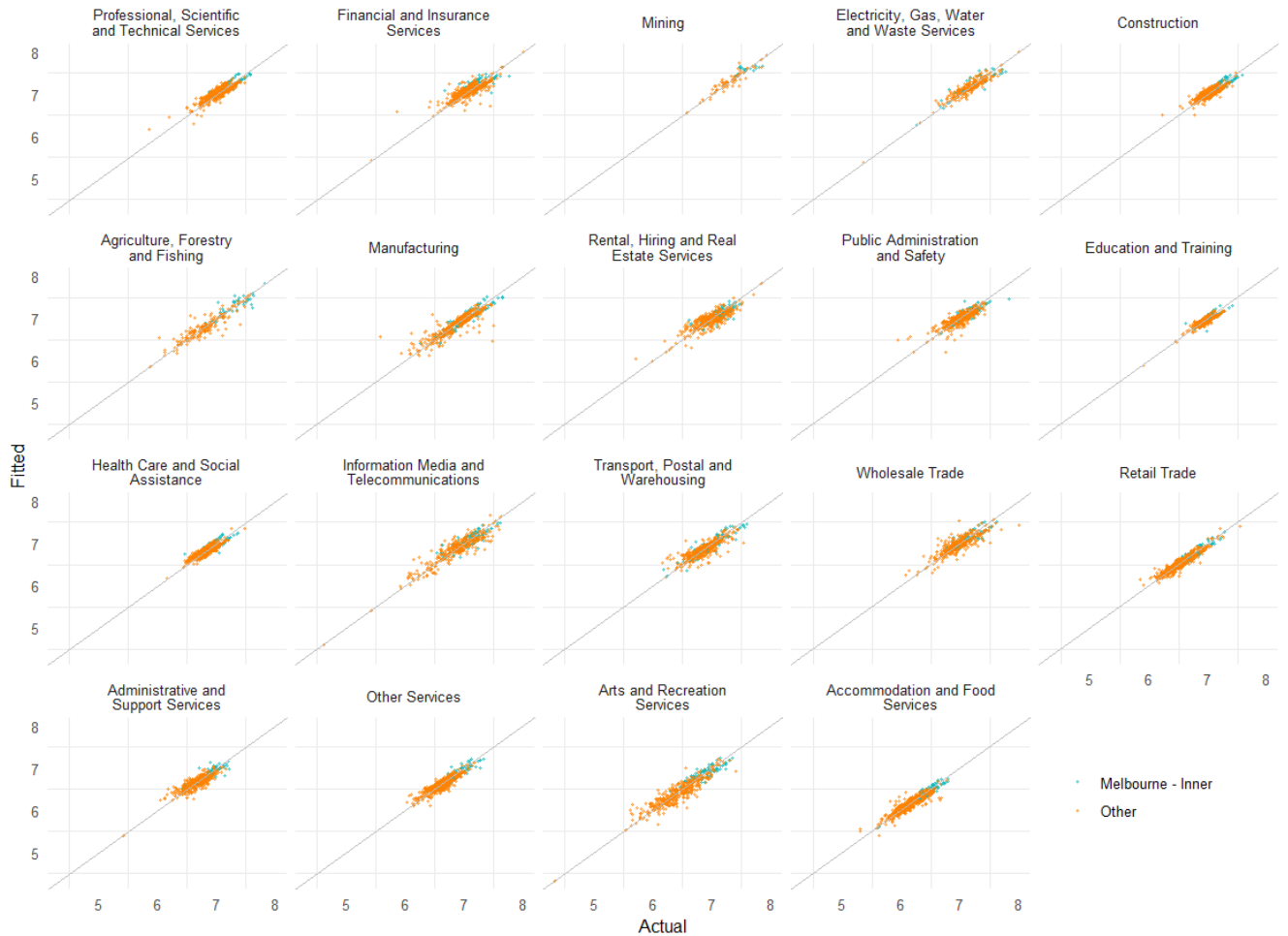
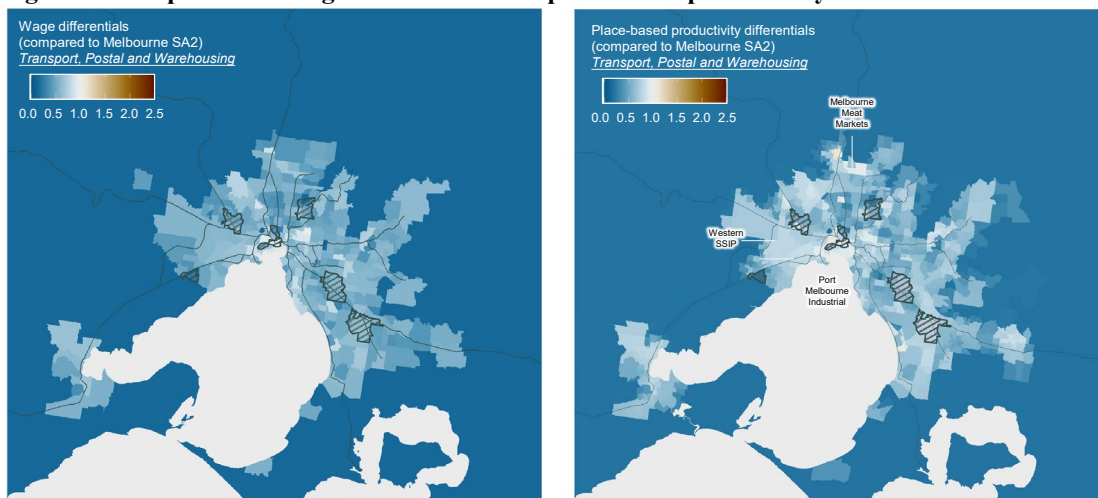


Figure 2: Comparison of wage differentials and place-based productivity differentials



5. Contributions and application in transport economic appraisal

There is currently no endorsed methodology for quantifying M2MLPJ for transport economic appraisals in Australia due to the absence of robust estimates of productivity differentials as

noted by ATAP guidelines. Leading practice from the UK TAG currently also does not provide the level of spatial disaggregation required by ATAP standards, nor does it consider the industrial variation in place-based productivity differentials required for a robust estimate.

This paper provides robust estimates for place-based productivity differentials required to quantify M2MLPJ (WEB2b) in Greater Melbourne, for each of the 19 ANZSIC industries and at a high level of spatial disaggregation. As such, they enable quantification of WEB2b in line with ATAP guidelines' stated standard for Melbourne. The method can potentially be adopted for other geographic regions such as the other Australian States and for Australia nationally.

It is worth noting that quantification of M2MLPJ should be built on sufficient justification and narrative. For example, why will the transport infrastructure investment of interest generate a M2MLPJ in the first place? The rationale and economic theory for individuals changing their location/industry of work as a result of the transport investment of interest should be adequately discussed before quantification is undertaken. For example, transport investments change travel times and individuals may choose to change jobs to maximise their own utility, such as to reduce their personal travel times. In instances where individuals change jobs to a location with more productive place-based attributes (namely, agglomeration and natural endowments) for that given industry, their output and hence the portion of wage attributable to place-based attributes will increase. Part of this output accrues to the government as tax revenue and this forms the benefit that M2MLPJ captures.

Appendix

Table 4: Average productivity differentials summarized by SA4 and industry

SA4 / Industry	Construction	Retail Trade	Accommodation and Food Services	Transport, Postal and Warehousing	Financial and Insurance Services	Professional, Scientific and Technical	Public Administration and Safety	Education and Training	Health Care and Social Assistance	Arts and Recreation Services
Melbourne - Inner	0.9	1.16	0.97	0.76	0.88	0.86	0.88	0.93	0.93	0.84
Melbourne - West	0.75	0.89	0.68	0.56	0.47	0.72	0.75	0.76	0.68	0.38
Melbourne - North West	0.69	0.76	0.63	0.41	0.43	0.62	0.59	0.6	0.6	0.27
Melbourne - North East	0.69	0.76	0.58	0.41	0.39	0.63	0.55	0.67	0.63	0.28
Melbourne - Inner East	0.78	1.07	0.79	0.62	0.79	0.8	0.82	0.87	0.85	0.55
Melbourne - Outer East	0.73	0.89	0.67	0.53	0.68	0.72	0.61	0.8	0.72	0.48
Melbourne - Inner South	0.78	1.02	0.86	0.63	0.83	0.77	0.75	0.88	0.81	0.67
Melbourne - South East	0.77	0.97	0.69	0.53	0.56	0.73	0.68	0.82	0.72	0.48

References

- Johnson D, Dargay J, and Reilly K (2008) *Real regional productivity differentials for use in transport appraisal*, European Transport Conference 2008 Proceedings
- Transport and Infrastructure Council (2021) *Australian Transport Assessment and Planning Guidelines (ATAP): Wider Economic Benefits T3*
- Laird J, Venables T and Johnson D (2019) *Move to More/Less Productive Jobs*