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Transport poverty and subjective wellbeing☆

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ABSTRACT

Using 12 waves of longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, we examine the relationship between transport poverty and subjective wellbeing. To measure transport poverty, we use indicators that reflect transport affordability and accessibility. Our preferred two-stage least squares (2SLS) estimates, which instrument for transport poverty using NYSE Arca Oil Stock Prices and OPEC oil supply (in millions of barrels), suggest that a standard deviation increase in transport poverty is associated with a decline in subjective wellbeing between 0.318 and 0.544 standard deviations. This general finding is robust to alternative ways of measuring transport poverty, alternative estimation approaches, alternative approaches to addressing endogeneity of transport poverty, and holds irrespective of whether subjective wellbeing is measured using the single-item overall life satisfaction scale or composite scales such as the Mental Health Inventory (MHI-5) scale or the Kessler Psychological Distress Scale (K10).

1. Introduction

Subjective wellbeing refers to judgments by an individual of his or her satisfaction with their life, feelings of happiness and sadness, as well as other negative and positive emotions (Diener, 1984; Kahneman et al., 1999). Subjective wellbeing has been linked to a broad range of positive outcomes, most notably good physical health, rewarding personal relationships, strong work engagement and longevity among others (see, Diener et al., 2017; Lyubomirsky et al., 2005). Improving subjective wellbeing has become an important policy objective in many countries with some suggesting that the ultimate goal of government should be to improve the wellbeing, happiness and quality of life of its citizens, rather than focus on more conventional economic indicators, such as economic growth (Diener, 2000, 2006; Kahn and Juster, 2002). In Australia, the country in which we situate our study, one survey shows that 77% of Australians believe that the prime objective of government should be to maximize people's happiness, rather than maximize the country's wealth (Hamilton and Rush, 2006).

Transport poverty encompasses various deprivations relating to transport access and affordability (Mattioli et al., 2017). The term has been used synonymously with other transport-related concepts, such as car economic stress, transport disadvantage, transport-related social exclusion, transport accessibility and transport affordability among others (see, Currie et al., 2009; Hine and Mitchell, 2017; Lucas et al., 2016, 2018; Preston and Rajé, 2007; Xia et al., 2016). In the context of developed countries, such as Australia,

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transport poverty has typically been used to refer to scenarios in which a disproportionate amount of household income is spent on transport costs in order to access essential services, travel to work and engage in social activities (Gleeson and Randolph, 2002; Mattioli et al., 2017). We use the term 'transport poverty' in this more narrow sense to refer to the situation in which households find it difficult to meet the cost of transportation.

Transport is derived demand in the sense that mobility facilitates education and job opportunities, access to essential services, such as health care, and involvement in social activities (Mattioli et al., 2017). Difficulties accessing, and paying for, transport have been linked to a range of poor life outcomes (Mattiolo et al., 2017), which previous research has shown to be associated with lower subjective wellbeing (Dolan et al., 2008). For example, previous research has documented that difficulties accessing transport are linked to reduced participation in higher education and training (Kenyon, 2011), reduced access to health services (Mackett and Thoreau, 2015), higher rates of unemployment, lower involvement in social activities and less engagement with social networks (Farber and Paez, 2009), often resulting in isolation (Farber et al., 2018; Lucas, 2012; Lucas et al., 2016). There are also likely to be stress-related costs associated with allocating a high proportion of the household budget to transport costs, which lower subjective wellbeing.

Yet, despite the importance of affordable transport for one's quality of life, little attention has been devoted to examining the relationship between transport and subjective wellbeing. A recent survey of the literature concludes that most studies that examine the role of transport in shaping wellbeing focus on travel satisfaction (De Vos et al., 2013). Previous studies have focused on the relationship between commuting time and subjective wellbeing (see, e.g., Lorenz, 2018; Zhu et al., 2018), the relationship between travel behaviour and wellbeing (Mahoney, 2015), and how alternative forms of transportation (e.g., bus, cycling and walking) are related to subjective wellbeing (Jones et al., 2012; Ma et al., 2018). A body of literature examines the determinants of transport poverty (see, e.g., Lucas et al., 2018; Martens, 2013), and another strand of literature examines the effects of transport poverty on particular social outcomes (see, e.g., Lucas et al., 2016).

We use 12 waves of longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) survey to examine the relationship between transport poverty and subjective wellbeing. Our measures of transport poverty reflect transport affordability and accessibility, and capture expenditure associated with both public and private transport. We pay particular attention to addressing endogeneity of transport poverty using both external and internal instruments and alternative matching methods. Using self-reported information on life satisfaction to proxy subjective wellbeing, we find that an increase in transport poverty is associated with lower levels of subjective wellbeing. Specifically, our preferred two-stage least squares (2SLS) estimates, which instrument for transport poverty using NYSE Arca Oil Stock Prices and OPEC oil supply (in millions of barrels), suggest that a standard deviation increase in transport poverty is associated with a decline in subjective wellbeing between 0.318 and 0.544 standard deviations, depending on the measure of transport poverty and/or instrument used. These results are robust to various extensions and sensitivity checks including estimation methods, alternative ways of measuring subjective wellbeing and transport poverty, and alternative approaches to addressing endogeneity of transport poverty, including propensity score matching (PSM) and heteroskedasticity-based identification.

Australia represents an interesting context in which to situate a study on transport poverty and subjective wellbeing. Australia is almost completely reliant on imported petroleum to meet its transport needs.[1] The combination of a weak Australian dollar and high excise taxes on fuel at the bowser have made fuel prices in Australia among the most expensive in the world. Soaring house prices, particularly in the inner suburbs of the large cities, have contributed to urban sprawl in which large numbers of low income households live in housing estates in the outer suburbs up to 50 km from the city centre and commute long distances to work each day. There is also a general lack of public transport infrastructure serving the outer suburbs in most of the major Australian cities. As Armstrong et al. (2015) put it: "Fringe developments are characterised by low housing and low employment density, limited (if any) mixed-use development and poor access to public transport. Together, this increases distances between where people live and where they need to travel for work, shopping, socialising and recreating". As a consequence, many relatively low-income households have no other option but to own cars which have often become very expensive to run with rising fuel prices, contributing to the incidence of transport poverty (Currie and Stanley, 2007).

Much of the literature on transport poverty has focused on the UK (see, e.g., Mattioli et al., 2017; RAC Foundation, 2012; Sustrans, 2012). We contribute to a small literature that has examined different aspects of transport poverty in Australia (see, Armstrong et al., 2015; Currie and Stanley, 2007; Currie et al., 2009, 2010; Rosier and McDonald, 2009; Xia et al., 2016). Most of these studies point to the existence of transport poverty, and discuss the reasons for it, in general terms. Xia et al. (2016) compare transport-related social exclusion in Perth and Sydney. The closest studies to ours are Currie et al. (2009, 2010) and Delbosc and Currie (2011) who explore the relationship between transport poverty, social exclusion and subjective wellbeing in Australia focussing on Melbourne and Victoria, respectively. We differ from these studies in that while Currie et al. (2010) use cross-sectional data for one city and Delbosc and Currie (2011) for one state, with relatively small samples, we employ longitudinal data that is nationally representative, with residents from all states and territories represented in the sample, and specifically seek to address endogeneity of transport poverty.

Increasing prevalence of transport poverty in developed countries has made transport poverty a major policy concern. For instance, in the UK, one influential study found that as many as four-fifths of households are in transport poverty (RAC Foundation, 2012). In the HILDA survey across all waves 8% of households were in transport poverty, although in some waves this figure was as high as 12% and many of these are low-income earners. Our results are important because they document that there is a causal

[1] A recent estimate is that 91% of Australia's transport fuel (petrol and diesel) is imported either as oil to be refined in Australia or as refined fuel products (Commonwealth of Australia, 2015).

relationship between transport poverty and lower subjective wellbeing. The effects in our preferred 2SLS estimates are large. We find that the negative effect of living in transport poverty on subjective wellbeing is comparable to, or stronger than, the effects of educational status, income, being (un)employed or suffering a major illness. Our results provide support for calls for improved transport infrastructure and services, and other measures to address transport poverty, such as transport vouchers (Serebrisky et al., 2009), in particular in outer suburban areas.

The rest of the paper is set out as follows. The next section provides an overview of the data and how the key variables are measured. The empirical methodology is set out in Section 3. The results are presented in Section 4. The final section concludes.

2. Data

We use longitudinal data from the HILDA survey, which is a nationally representative household-based panel study that targets household formation, family, income, wealth, work and social-related dimensions of Australians aged 15 years and above. The survey commenced in 2001 and has run annually since (see, Watson and Wooden, 2012 for details on survey design). We use Release 16 of the survey which includes 16 waves of annual data from 2001 to 2016. However, we restrict our analysis to waves 5–16, which are the only waves with information on both subjective wellbeing and transport poverty. Our analysis is also restricted to respondents who are included in a least two waves of the survey, leaving us with a working sample of 178,480 observations on 23,127 individuals.

2.1. Subjective wellbeing

Our main measure of subjective wellbeing comes from responses to a single-item question that captures overall life satisfaction of respondents. Specifically, the HILDA survey asks the question: ‘All things considered, how satisfied are you with your life?’ Respondents report scores to this question on a scale of 0–10, in which zero is ‘totally dissatisfied’ and 10 is ‘totally satisfied’. Responses to the life satisfaction question refer to reflections on life as a whole, rather than experience of pleasant emotions (Fujita and Diener, 2005). As Diener et al (1999) discuss, while single item scales are not the most valid measures of subjective wellbeing available, responses to overall life satisfaction have been found to have adequate reliability and validity. Questions of this sort are typically used as proxies for subjective wellbeing in studies such as this by economists and psychologists because of their established reliability and validity, and their availability in large-scale surveys. The distribution of responses on overall life satisfaction is shown in Fig. A1. The average life satisfaction score in the HILDA survey of 7.91 out of 10 with a standard deviation of 1.45 is consistent with observed norms in western adult samples (Cummins, 1995).

In robustness checks, instead of using overall life satisfaction, we employ the five-item Mental Health Inventory (MHI-5) scale, which is a subscale of the short form (SF-36) general health survey, and the Kessler Psychological Distress Scale (K10) to measure subjective wellbeing. We find that our results are robust to using these alternative measures.

2.2. Transport poverty

The literature discusses various aspects of transport poverty including mobility poverty (Martens, 2013; Velaga et al., 2012), accessibility poverty (Lucas et al., 2018; Martens and Bastiaanssen, 2014) and transport affordability (Litman, 2015; Lucas et al., 2016). Mobility poverty refers to the lack of transport, while accessibility poverty refers to the difficulty of reaching important locations and activities such as employment, social activities and health care services. Transport affordability refers to the inability to meet the costs of transport.

Our main measures of transport poverty are based on transport affordability, although in robustness checks we also adopt measures that reflect accessibility poverty. The most commonly used measure of transport poverty capturing transport affordability reflects actual transport expenditure as a share of income. Gleeson and Randolph (2002, p. 102) argue that “transport poverty occurs when a household is forced to consume more travel costs than it can reasonably afford, especially costs relating to motor car ownership and usage”. Akin to the definition of fuel poverty, households are considered ‘transport poor’ if they spend more than 10% of their income on transport-related expenditure (Lucas et al., 2016).

Since the fifth wave of HILDA, respondents have been asked about their annual household expenditure on: (1) public transport and taxis, and (2) motor vehicle fuel. Our first measure of transport poverty (POV1) is a dummy variable set equal to one if households spend more than 10% of their income on public transport and taxis, while our second measure of transport poverty (POV2) is a dummy variable set equal to one if households spend more than 10% of their income on motor vehicle fuel. We also use a third measure of transport which is based on total transport-related expenditure derived by taking the sum of household expenditures on public transport, taxis and motor vehicle fuel. We use a dummy variable (POV3) set equal to one if households spend more than 10% of their income on transport-related expenditure, consisting of expenditure on public transport, taxis and motor vehicle fuel.

Table A1 presents data on mean subjective wellbeing by transport poverty. This table lends preliminary support to the idea that transport poverty is generally associated with lower mean subjective wellbeing. This preliminary observation, however, does not take into account other factors that influence subjective wellbeing. Thus, consistent with the subjective wellbeing literature, we also control for relevant covariates that are likely to affect an individual’s subjective wellbeing, which are discussed in the next section.

2.3. Covariates

A large literature has examined factors correlated with life satisfaction (see Dolan et al., 2008 for a review). In addition to transport poverty, in all specifications, we include a full set of variables correlated with subjective wellbeing, consistent with the existing literature. These include age and its quadratic term, income, marital status, educational status and employment status, among others. Table A2 provides full details on the control variables.

3. Empirical strategy

We estimate the following subjective wellbeing equation:

$$SWB_{ijt} = \beta_1 TP_{Jt} + \sum_n \beta_n \boldsymbol{X}_{n,it} + \vartheta_i + \alpha_s + \mu_t + \varepsilon_{ijt} \tag{1}$$

where SWB is reported life satisfaction of respondent i in household j at time (i.e., wave) t; TP is the measure of transport poverty; X is a set of control variables that are known to influence subjective wellbeing; ε is the error term; ϑ_i represents controls for time-invariant unobserved individual characteristics; α_s and μ_t are dummy variables that control for unobserved state and wave characteristics, respectively. Our baseline estimates are based on pooled ordinary least squares (OLS) that control for wave and state fixed effects and a panel fixed effect (FE) model that controls for wave, state and individual fixed effects as well as omitted variable bias.

If transport poverty is endogenous, the pooled OLS estimates will be biased. One potential source of endogeneity is measurement error in estimating transport poverty. This will occur if households do not perfectly recall their expenditure on motor fuel, public transport and taxis, which is very likely. Previous research suggests that HILDA respondents under estimate their annual expenditure on energy bills by between 13 and 20 per cent (Wilkins and Sun, 2010). Another potential source of endogeneity is simultaneity bias. For example, 'happier' people may earn more, reducing the share of transport expenditure in their overall household budget. In addition, the opportunity cost of time for 'happier' people might be higher, which influences their relative expenditure on different modes of transport. Endogeneity may also emerge as a result of omitted variables or unobservable factors for which one cannot account. In the context of our analysis, this is plausible given the relatively low R-squared in the baseline model.

Hence, given that transport poverty is likely to be endogenous, we also adopt alternative estimation approaches that address endogeneity. Our main identification strategy is to instrument for transport poverty using an oil stock index and oil supply in a 2SLS framework. Specifically, we use the NYSE Arca Oil Stock Prices and OPEC oil supply in millions of barrels as external instruments. The former is an index of stocks of leading companies that are involved in the exploration and production of oil listed on the NYSE and, thus, proxies the performance of the oil industry. The latter is a proxy for the global supply of oil.

A valid instrument must satisfy two assumptions. First, it must be correlated with transport poverty. Second, it must be orthogonal to the error term in Eq. (1). Intuitively, the stock price of major oil suppliers in the world is likely to be correlated with fuel prices and thus, transport poverty. However, movements in NYSE Arca Oil Stock prices are unlikely to be directly related to the subjective wellbeing of any individual in the sample. Thus, if stock prices of oil suppliers change, the only mechanism via which such changes will affect subjective wellbeing will be through fuel prices and, hence, the expenditure share of transport in the household budget on which we base our transport poverty measures.[2] Australia imports almost all of its refined petroleum and fuel prices are sensitive to OPEC decisions to restrict supply. Thus, we expect changes in the supply of oil by OPEC to be correlated with transport poverty. However, OPEC oil supply should not directly influence subjective wellbeing.

In robustness checks, we also adopt the Lewbel (2012) heteroskedasticity-based identification approach. Lewbel (2012) shows that internally generated instruments can be constructed from the residuals of auxiliary equations, which are multiplied by included exogenous variables (X_i) in mean-centred form ($\bar{X}$). The estimation problem is as follows:

$$SWB_i = \alpha + X^{'}\beta_1 + S_i\gamma_1 + \epsilon_1 \quad \epsilon_1 = \alpha_1 U + V_1 \tag{2}$$

$$TP_i = X^{'}\beta_2 + \epsilon_2 \quad \epsilon_2 = \alpha_2 U + V_2 \tag{3}$$

such that SWB_i, as defined previously, is an individual's overall life satisfaction and TP_i is the measure of our endogenous variable (i.e., transport poverty). U denotes the individual's unobserved social environment that affects both transport poverty and life satisfaction. V_1 and V_2 are idiosyncratic errors. $X^{'}$ is a vector of control variables.

Lewbel (2012) argues that internally generated instruments (Z_i) given by:

$$Z_i = (X_i - \bar{X})\cdot\varepsilon$$

can be used, where ε has zero covariance with regressors and represents a vector of first-stage regression residuals of each endogenous regressors on all exogenous regressors. Thus, the mean of each internally generated instrument will be zero. A precondition for

[2] There are no data, of which we are aware, on the proportion of Australians who hold shares in NYSE Arca oil stocks. In 2017, a survey found that 8% of Australians held shares listed on stock markets outside Australia, up from 5% in 2014. However, as the survey compilers acknowledge, this likely represents an upper bound because some respondents may have interpreted the question as asking if they held shares in international companies listed on the Australian Stock Exchange (Deloitte Access Economics, 2017, p.4). From these figures, it is reasonable to infer that the proportion of Australians holding shares on the NYSE, and specifically in NYSE Arca oil stocks, and, hence, whose subjective wellbeing may be directly influenced by movements in those stocks, is very low. It could be argued that movements in NYSE oil stocks could influence movements in oil stocks on the Australian Stock Exchange and, thus, influence the subjective wellbeing of individuals holding Australian shares. But, in 2017 less than one third (31%) of Australians owned shares (Deloitte Access Economics, 2017) and most of these were so-called 'mum and dad' investors who typically have very small shareholdings in one or two privatized former government-owned companies, such as Qantas and Telstra.

identification in the Lewbel (2012) 2SLS approach is the presence of heteroskedasticity, and in the data used in this study, the Breusch and Pagan (1979) test for heteroskedasticity is statistically significant throughout, suggesting that the heteroskedasticity assumption is fulfilled.

As an alternative to instrumenting for transport poverty, we also use PSM as an additional approach to address endogeneity. PSM is routinely used in the literature to address endogeneity in non-experimental data (see, e.g., Campello et al., 2010; Kam and Palmer, 2008; Maertens and Swinnen, 2009). We apply Rosenbaum and Rubin's (1983) PSM technique with different matching algorithms to determine the average effect of the treatment (in our case individuals who live in households that are not transport poor) on life satisfaction. In order to draw causal inferences about the effect of transport poverty on subjective wellbeing using PSM, we ask the question: What is the outcome (in terms of life satisfaction) for an individual who lives in a household that is treated (i.e., that is not transport poor), relative to the hypothetical outcome that would have prevailed if the same individual was transport poor? We estimate the average treatment effect as follows:

$$\tau \equiv E\{O_1 - O_0|B = 1\}$$

$$= E\{E\{O_1 - O_0|B = 1, p(W)\}\}$$

$$= E\{E\{O_1|B = 1, p(W) - E\{O_0|B = 0, p(W)\}|B = 1\}$$

where τ is the average effect of the treatment, B is a binary variable equal to one for a household that is not transport poor and zero otherwise, O represents life satisfaction, and W is a vector of pre-treatment characteristics represented by relevant covariates.

The propensity score, $p(W)$, captures the probability of having lower life satisfaction given pre-treatment characteristics (W). We use different matching methods, including nearest neighbour, radius and kernel matching methods to ensure robust findings.

4. Results

4.1. Baseline results

Table 1 presents baseline results for the relationship between transport poverty and life satisfaction. Columns 1 and 2 present pooled OLS and panel fixed effect (FE) results, respectively, for the relationship between POV1 and life satisfaction. Columns 3 and 4 present pooled OLS and panel FE results, respectively, for the relationship between POV2 and life satisfaction, while Columns 5 and 6 report pooled OLS and panel FE results, respectively, for POV3.

Overall, results from Table 1 suggest that transport poverty is associated with lower life satisfaction. In Columns 1 and 2, the coefficients on POV1 are negative with effect sizes of 0.197 (with p-value of 0.000) and 0.068 (with p-value of 0.048), respectively. This implies that, on average, individuals who live in households that spend more than 10% of their household income on public transport and taxis have 0.068–0.197 lower life satisfaction on a 0–10 scale. In terms of standardized coefficients, a one standard deviation increase in POV1 is associated with declines of 0.014 and 0.005 standard deviations in life satisfaction in Columns 1 and 2, respectively.

The coefficient on POV2 is statistically significant only in Column 3 with a negative coefficient of 0.049 (with p-value of 0.002). The result in column 3 implies that, on average, individuals who live in households that spend more than 10% of their household income on motor vehicle fuel have 0.049 lower life satisfaction on a 0–10 scale. A one standard deviation increase in POV2 is associated with a decline of 0.008 standard deviations in life satisfaction.

In columns 5 and 6, the coefficients on POV3 are negative with effect sizes 0.030 (with p-value of 0.038) and 0.025 (with p-value of 0.055), respectively. This result implies, on average, 0.025–0.030 lower life satisfaction on a scale of 0–10 for individuals who live in households that spend more than 10% of their household income on transport-related expenditures. In terms of standard deviation changes, a one standard deviation increase in POV3 is associated with declines of 0.006 and 0.005 standard deviations in life satisfaction in Columns 5 and 6, respectively.

The effects of the covariates in Table 1 are generally consistent with what one would expect and with findings in the existing literature (see, Dolan et al., 2008), which increases confidence in our findings. In particular, life satisfaction is at a minimum around 42–43 years old, females have higher life satisfaction than males, those with a major illness have lower life satisfaction and relative to those who are married (reference case), respondents who are single, divorced, separated or widowed have lower life satisfaction.

4.2. Addressing endogeneity

Next, we examine the sensitivity of our results to endogeneity using oil stock prices and OPEC oil supply as instruments. Table 2 Panel A presents results for 2SLS regressions with oil stock prices as the instrument, Panel B reports results using the OPEC oil supply as the instrument, while Panel C reports results for estimates that combine both instruments. First stage results suggest that both instruments are correlated with transport poverty. An increase in oil stock prices is associated with an increase in transport poverty while an increase in oil supply is associated with a decline in transport poverty. Across all panels, our instruments are not weakly correlated with transport poverty (Stock and Yogo, 2005), while in Panel C, at the 5% significance level, we do not reject the null hypothesis for the overidentifying restriction test except in Column 2, and thus results in this column should be treated with caution.

Results from Table 2 suggest that endogeneity generates considerable downward bias in our baseline estimates given that the 2SLS estimates are relatively larger in magnitude than both the pooled OLS and panel FE estimates. In Panel A, a one standard

Table 1
Transport Poverty and Life Satisfaction (Baseline Results).

VARIABLES	(1) Pooled OLS	(2) Panel FE	(3) Pooled OLS	(4) Panel FE	(5) Pooled OLS	(6) Panel FE
POV1	−0.197***	−0.068**				
	(0.040)	(0.034)				
	[-0.014]	[-0.005]				
POV2			−0.049***	0.003		
			(0.016)	(0.015)		
			[-0.008]	[0.001]		
POV3					−0.030**	−0.025*
					(0.015)	(0.013)
					[-0.006]	[-0.005]
Female	0.081***		0.081***		0.081***	
	(0.007)		(0.007)		(0.007)	
Age	−0.070***	−0.045***	−0.070***	−0.046***	−0.070***	−0.045***
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)
Age squared	0.082***	0.038***	0.083***	0.038***	0.082***	0.038***
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)
Dependants	−0.042***	−0.032***	−0.042***	−0.032***	−0.042***	−0.032***
	(0.004)	(0.007)	(0.004)	(0.007)	(0.004)	(0.007)
Separated	−0.735***	−0.552***	−0.733***	−0.550***	−0.735***	−0.551***
	(0.026)	(0.038)	(0.026)	(0.038)	(0.026)	(0.038)
Divorced	−0.427***	−0.248***	−0.423***	−0.247***	−0.426***	−0.248***
	(0.017)	(0.039)	(0.017)	(0.039)	(0.017)	(0.039)
Widowed	−0.268***	−0.298***	−0.264***	−0.295***	−0.268***	−0.296***
	(0.020)	(0.055)	(0.020)	(0.055)	(0.020)	(0.055)
Single	−0.342***	−0.254***	−0.343***	−0.255***	−0.343***	−0.255***
	(0.011)	(0.018)	(0.011)	(0.018)	(0.011)	(0.018)
Income	0.158***	0.052***	0.171***	0.056***	0.161***	0.050***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
Employed	0.075***	0.047***	0.073***	0.046***	0.075***	0.047***
	(0.009)	(0.012)	(0.009)	(0.012)	(0.009)	(0.012)
Postgrad	−0.126***	0.038	−0.129***	0.038	−0.128***	0.038
	(0.015)	(0.044)	(0.015)	(0.044)	(0.015)	(0.044)
Graduate Diploma	−0.043***	0.012	−0.045***	0.013	−0.044***	0.012
	(0.014)	(0.045)	(0.014)	(0.045)	(0.014)	(0.045)
Bachelor	−0.097***	−0.066**	−0.099***	−0.066**	−0.099***	−0.066**
	(0.010)	(0.028)	(0.010)	(0.028)	(0.010)	(0.028)
Diploma	−0.045***	−0.027	−0.045***	−0.025	−0.045***	−0.026
	(0.012)	(0.039)	(0.012)	(0.039)	(0.012)	(0.039)
Certificate	−0.047***	−0.046*	−0.047***	−0.046*	−0.047***	−0.046*
	(0.009)	(0.026)	(0.009)	(0.026)	(0.009)	(0.026)
Illness	−0.570***	−0.177***	−0.569***	−0.177***	−0.570***	−0.177***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Constant	7.641***	8.623***	7.492***	8.588***	7.610***	8.646***
	(0.069)	(0.112)	(0.071)	(0.114)	(0.072)	(0.114)
Observations	178,480	178,480	178,359	178,359	178,325	178,325
R-squared	0.081	0.012	0.081	0.012	0.081	0.012
Number of Individuals	23,127	23,127	23,126	23,126	23,126	23,126

All regressions control for state and wave fixed effects while Panel FE regressions control for individual fixed effects.
Reference category for marital status are those married or in a de facto relationship, for educational status it is those whose highest education level is year 12 or below, and for employment status it is those unemployed or not in the labour force.
Robust standard errors in parentheses. Individual clustered standard errors are reported for FE models.
Standardized coefficients in brackets.

* Denotes p-value < 0.1.
** Denotes p-value < 0.05.
*** Denotes p-value < 0.01.

deviation in transport poverty is associated with a decline in life satisfaction between 0.388 and 0.544 standard deviations, depending on how transport poverty is measured. In Panel B, transport poverty is associated with a decline in life satisfaction of 0.318 and 0.324 standard deviations, depending on whether transport poverty is measured by POV1 or POV3, respectively. In Panel C, transport poverty is associated with a decline in life satisfaction between 0.375 and 0.466 standard deviations, depending on how transport poverty is measured.

Table 3 reports PSM results using four different matching methods, which also support the conclusion from the 2SLS estimates that transport poverty has a negative effect on life satisfaction. Specifically, results here suggest that, on average, individuals that live in households that are not poverty poor tend to have relatively higher levels of wellbeing.

Table 2
Transport Poverty and Life Satisfaction (IV Results).

VARIABLES	(1) POV1	(2) POV2	(3) POV3
Panel A – 2SLS with external instrument (Oil Index)			
Transport Poverty	−7.402***	−2.804***	−2.078***
	(1.728)	(0.631)	(0.453)
	[−0.544]	[−0.456]	[−0.388]
Observations	178,480	178,359	178,325
First stage			
Instrument	0.018***	0.049***	0.066***
	(0.002)	(0.005)	(0.005)
R-squared	0.1034	0.1137	0.1440
F-statistics	72.55	116.32	167.28
Panel B – 2SLS with external instrument (OPEC Oil Supply)			
Transport Poverty	−4.322***	0.892	−5.089***
	(0.913)	(2.241)	(1.237)
	[−0.318]	[0.145]	[−0.324]
Observations	178,480	178,359	178,325
First stage			
Instrument	−0.155***	−0.258***	−0.094***
	(0.010)	(0.075)	(0.023)
R-squared	0.1568	0.0568	0.2113
F-statistics	219.04	11.85	116.60
Panel C – 2SLS with Oil Index & OPEC Oil Supply			
Transport Poverty	−5.101***	−2.491***	−2.494***
	(0.817)	(0.614)	(0.449)
	[−0.375]	[−0.406]	[−0.466]
Observations	178,480	178,359	178,325
First stage			
F-statistics	129.44	61.90	87.04
J p-value	0.0937	0.0412	0.1709

Notes: In each column, the dependent variable is subjective wellbeing.
All regressions include the relevant control variables and control for the relevant fixed effects as in Table 1.
Labels on top of each column represent the measure of transport poverty.
Standard errors in parentheses.
Standardized coefficients in brackets.
*Denotes p-value < 0.1.
**Denotes p-value < 0.05.
*** Denotes p-value < 0.01.

Table 3
PSM results with different matching methods.

Matching method	ATT (average treatment effect on the treated) POV1	POV2	POV3
1 - Nearest Neighbour (one-to-one)	0.205***	0.040***	0.066***
	(0.008)	(0.015)	(0.007)
4 - Nearest Neighbour	0.224***	0.041***	0.059***
	(0.014)	(0.015)	(0.001)
Radius	0.233***	0.040	0.062***
	(0.038)	(0.053)	(0.006)
Kernel	0.242***	0.039***	0.066***
	(0.029)	(0.009)	(0.006)

Standard errors in parentheses.
*Denotes p-value < 0.1.
**Denotes p-value < 0.05.
*** Denotes p-value < 0.01.

4.3. Robustness checks

In this section, we examine the robustness of our results to alternative ways of modelling the hypothesised relationship, alternative ways of measuring subjective wellbeing and transport poverty and using Lewbel's (2012) heteroscedasticity identification approach.

Panel A of Table 4 presents results for the association between transport poverty and subjective wellbeing using ordered logit, instead of pooled OLS. Ferrer-i-Carbonell and Frijters (2004) suggest that subjective wellbeing regressions are not sensitive to whether subjective wellbeing is treated as cardinal or ordinal. The results in Panel A, which are consistent with our baseline estimates in Table 1, confirm that this is the case with our data.

Next, we employ the Lewbel (2012) approach as a robustness check on the 2SLS results with external instruments. We report Lewbel 2SLS results that: (1) use internal instruments only (Panel B), (2) combine oil stock prices with internally generated instruments (Panel C), (3) combine OPEC oil supply with internally generated instruments (Panel D), and (4) combine oil stock prices, oil supply and internally generated instruments (Panel E). The results reinforce the conclusion that transport poverty has a negative effect on subjective wellbeing.

Existing research has shown that time-invariant personality traits have a large influence on subjective wellbeing (Diener and Lucas, 1999; Ferrer-i-Carbonell and Frijters, 2004; Schimmack et al., 2004). While, to a large extent, the use of panel FEs should control for this (see Ferrer-i-Carbonell and Frijters, 2004), we take advantage of the fact that waves 5, 9 and 13 of HILDA contain the Big-Five Personality Inventory scale, and, hence, we control for personality. The Big-Five personality traits (extraversion, conscientiousness, agreeableness, emotional stability and openness to experience) are measured on a 1–7 scale. The results for transport poverty, together with the findings for the Big-Five, for these three waves are reported in Panel F of Table 4. We find that each personality trait of the Big-Five is positively correlated with subjective wellbeing. This finding is consistent with previous studies that have found positive wellbeing effects of various personality traits, especially emotional stability and extraversion (see, e.g., Diener and Lucas, 1999; González Gutiérrez et al., 2005; Ha and Kim, 2013; Vittersø, 2001). Our results also show that the effect of emotional stability is the strongest, consistent with previous research (see, e.g., Vittersø, 2001). The association between transport poverty and life satisfaction remains generally consistent with the baseline results.

Income is also likely to be endogenous (‘happier’ people are likely to earn more). To address endogeneity of income, some studies resort to the exclusion of income as a control variable from subjective wellbeing regressions (e.g., Boyd-Swan and Herbst, 2012) while others instrument for income using variables such as father’s education (e.g., Knight et al., 2009). We report results from alternative specifications in which we: (1) exclude income, and (2) instrument for income using father’s education. Panel G reports results for regressions that exclude income, while Panel H report results for regressions that control for endogeneity of income. The results for transport poverty are consistent with the baseline estimates.

Currie et al. (2009, 2010) show that people who live in the outer suburbs of major cities are the most vulnerable to transport poverty. Currie et al. (2009) found that transport costs are a “major issue” for low-income households that own two or more cars in the outer suburbs of Melbourne and that for these households, transport costs represented “as much as 50% (or more) of total income” (Currie et al., 2009, p. 99). In Panel I of Table 4, we examine the relationship between transport poverty and subjective wellbeing for respondents who live in the outer suburbs of big cities. To do so we include an interraction term between dummy variables denoting those who live in the outer suburbs and are transport poor.

In Columns 1, 2 and 3 we interact the dummy variable capturing respondents in outer suburbs with POV1, POV2 and POV3, respectively. The interraction term was dropped in Column 1 as a result of collinearity and was statistically insignificant in Column 3; however, it is significant with a negative sign in Column 2. Taking into account the magnitude and sign on the coefficient of the interaction term, relative to other coefficients in the model, our results suggest that those who live in outer suburban areas and are transport poor (based on expenditure on motor vehicle fuel) tend to have lower levels of subjective wellbeing compared to those who are not. This makes sense, given that those who live in the outer suburbs are most reliant on owning a car to travel for work and leisure.

We consider the effects of labour market characterisitics. Specifically, it is likely that workers who commute to work daily might experience different effects of transport poverty than older people who are retired or those who are unemployed and do not commute often. Thus, we examine if the employed experience different effects compared to those who are unemployed or those not in the labour force. To do this, we include an interraction term between dummy variables denoting those who are employed and are transport poor. These results are reported in Panel J of Table 4. The results suggest that those who live in transport poverty and are employed tend to have lower levels of subjective wellbeing compared to those who are unemployed or not in the labour force. In Table 5, we report results from a series of tests that use alternative measures of subjective wellbeing and transport poverty. Following the approach in Welsch and Biermann (2017), we examine the robustness of our results to measuring life satisfaction as a dummy, in which we code respondents that report life satisfaction scores of 6–10 as ‘satisfied’ and scores of ‘0-5’ as ‘not satisfied’. Results for this exercise, in which we use a probit regression to estimate subjective wellbeing, are reported in Panel A and are consistent with the baseline results. We also conduct a similar exercise where we use a dummy variable, in which we code respondents that report life satisfaction scores above the mean value of 7.907 as ‘satisfied’ and below the mean as ‘not satisfied’. Results for this exercise, reported in Panel B of Table 5 and are consistent with the baseline results.

Next, we examine the sensitivity of our results to using a subjective measure of mental health as an alternative measure of subjective wellbeing. Given that transport poverty is likely to be a cause of isolation and social exclusion, it follows that one would expect transport poverty to be associated with poorer mental health. The HILDA survey provides information on a five-item Mental Health Inventory (MHI-5) scale, which is a subscale of the short form (SF-36) general health survey. The composite measure of subjective mental health, which is on a 0–100 scale, is based on a five-item questionnaire in which respondents were asked about how often in the past four weeks they have: (1) been nervous; (2) felt so down in the dumps that nothing could cheer them up; (3) felt calm and peaceful; (4) felt down; and (5) been happy. Panel C of Table 5 reports results for the association between transport poverty and mental health. Consistent with expectations, the results show that transport poverty is associated with poorer mental health, and are, thus, consistent with our main results.

Table 4
Robustness checks (Alternative Models).

VARIABLES	(1) POV1	(2) POV2	(3) POV3
Panel A – Ordered Logit Regressions			
Transport Poverty	−0.230***	−0.078***	−0.026
	(0.050)	(0.021)	(0.019)
	[−0.017]	[−0.013]	[−0.005]
Observations	178,480	178,359	178,325
Panel B – Lewbel 2SLS with internal instruments			
Transport Poverty	−0.205***	−0.026	−0.059**
	(0.049)	(0.026)	(0.024)
	[−0.015]	[−0.004]	[−0.011]
Observations	178,480	178,359	178,325
Panel C – Lewbel 2SLS with oil index and internal instruments			
Transport Poverty	−0.207***	−0.025	−0.060**
	(0.049)	(0.026)	(0.024)
	[−0.015]	[−0.004]	[−0.011]
Observations	178,480	178,359	178,325
Panel D – Lewbel 2SLS with OPEC oil supply and internal instruments			
Transport Poverty	−0.207***	−0.026***	−0.058**
	(0.049)	(0.008)	(0.024)
	[−0.015]	[−0.007]	[−0.011]
Observations	178,480	178,359	178,325
Panel E – Lewbel 2SLS with oil index, OPEC oil supply and internal instruments			
Transport Poverty	−0.209***	−0.041***	−0.060**
	(0.049)	(0.004)	(0.024)
	[−0.015]	[−0.009]	[−0.011]
Observations	178,480	178,359	178,325
Panel F – Controlling for the Big Five			
Transport Poverty	−0.176*	−0.087**	0.017
	(0.103)	(0.039)	(0.036)
	[−0.012]	[−0.014]	[0.003]
Extraversion	0.138***	0.138***	0.138***
	(0.015)	(0.015)	(0.015)
	[0.104]	[0.104]	[0.104]
Agreeableness	0.081***	0.081***	0.081***
	(0.016)	(0.016)	(0.016)
	[0.053]	[0.053]	[0.053]
Conscientious	0.045***	0.046***	0.046***
	(0.015)	(0.015)	(0.015)
	[0.033]	[0.033]	[0.033]
Emotional stability	0.151***	0.151***	0.151***
	(0.014)	(0.014)	(0.014)
	[0.116]	[0.115]	[0.116]
Openness	0.034**	0.033**	0.033**
	(0.016)	(0.016)	(0.016)
	[0.026]	[0.025]	[0.025]
Observations	36,916	36,888	36,883
Panel G – Excluding Income			
Transport Poverty	−0.119***	−0.035**	−0.058***
	(0.034)	(0.014)	(0.012)
	[−0.009]	[−0.006]	[−0.011]
Observations	178,480	178,359	178,325
Panel H – Controlling for Endogeneity of Income			
Transport Poverty	−0.243**	−0.036***	−0.046***
	(0.114)	(0.005)	(0.002)
	[−0.018]	[−0.006]	[−0.009]
Observations	155,694	155,584	155,554
Panel I – Outer Suburbs Effect			
Transport Poverty	−0.037	−0.042***	−0.028*
	(0.035)	(0.008)	(0.017)
	[−0.003]	[−0.007]	[−0.003]
Outer suburbs dummy	−0.117***	−0.124***	−0.120***
	(0.008)	(0.008)	(0.008)
	[0.035]	[0.037]	[0.035]
Suburban*Poverty		−0.074**	−0.025

(continued on next page)

Table 4 (*continued*)

VARIABLES	(1) POV1	(2) POV2	(3) POV3
	–	(0.029)	(0.018)
		[−0.014]	[−0.004]
Observations	178,480	178,359	178,325
Panel J – Labour market effect			
Transport Poverty	−0.820***	−1.194***	−0.971***
	(0.304)	(0.169)	(0.155)
	[−0.060]	[−0.194]	[−0.181]
Employed	0.074***	0.070***	0.072***
	(0.009)	(0.009)	(0.009)
	[0.024]	[0.023]	[0.024]
Employed*Poverty	−0.106***	−0.111***	−0.097***
	(0.031)	(0.016)	(0.015)
	[−0.075]	[−0.185]	[−0.185]
Observations	178,480	178,359	178,325

Notes: In each column, the dependent variable is life satisfaction. All regressions include the usual control variables. Labels on top of each column represent the measure of transport poverty. Standard errors in parentheses. Standardized coefficients in brackets.

* Denotes p-value < 0.1.

** Denotes p-value < 0.05.

*** Denotes p-value < 0.01.

As an alternative to measuring subjective wellbeing using life satisfaction, we also use the Kessler Psychological Distress Scale (K10), which was reported only in waves 7, 9, 11, 13 and 15 of the HILDA survey. The K10 is a 10–50 point scale that is derived from a 10-item questionnaire which reflects various dimensions of mental health including depression, psychological fatigue, nervousness and agitation (ABS, 2001). Panel D of Table 5 reports results for the association between transport poverty and K10. We find that transport poverty is associated with higher psychological distress (i.e., lower subjective wellbeing), and thus, findings from this exercise are consistent with our baseline estimates reported in Table 1.

We explore our baseline results through regressing life satisfaction on transport expenditure share of income and its quadratic, plus the usual covariates. We hypothesise a non-linear relationship between transport expenditure share of income and subjective wellbeing. As discussed above, expenditure on transport represents derived demand because it enables individuals to participate in a range of activities and build social interconnectedness that is associated with higher subjective wellbeing. Hence, we expect expenditure on transport to be associated with higher subjective wellbeing until a vertex is reached, after which point the share of income going to transport will be sufficiently high that subjective wellbeing will be lowered. The results are reported in Panel E of Table 5. Columns 1, 2 and 3 report the results for POV1, POV2 and POV3. The results confirm the non-linear relationship between transport poverty and subjective wellbeing. Specifically, we find an inverted U-shaped relationship between transport poverty, measured as the share of transport expenditure in the household budget, and subjective wellbeing.

We examine the robustness of our results to the use of 15% as an alternative threshold to the 10% threshold used in defining our main measures of transport poverty. The results are reported in Panel F of Table 5. The conclusions remain the same as the baseline estimates.

In a final check, in Panel G of Table 5, we adopt measures that reflect the accessibility poverty dimension of transport poverty. Measures of accessibility poverty are often subjective in nature and reflect an individual's perceived, or experienced, difficulty of reaching important locations and activities such as employment and health care services. We take advantage of two measures of accessibility poverty in the HILDA survey. The first is a dummy variable set equal to one if respondents agree that they had trouble getting a job because of transport problems or it was too far to travel (ACCESS1). The second is a dummy variable set equal to one if respondents indicated that they had not been looking for work in the last 4 weeks before the survey because of lack of transport (ACCESS2). Columns 1 and 2 report results for ACCESS1 and ACCESS2, respectively. Consistent with our main results, we find that accessibility poverty is associated with lower subjective wellbeing.

4.4. *The cost of transport poverty*

Our results robustly demonstrate a negative effect of transport poverty on wellbeing. In this section, as a guide to policy makers, we calculate the implied welfare cost to society of transport poverty. Specifically, we calculate shadow prices (or costs) to determine the compensating change in total household income required to offset the negative effect of an increase in transport poverty on wellbeing. This approach allows us to provide practical policy implications and relevant information allowing policy makers to understand the intangible costs of transport poverty. If we interpret wellbeing as a proxy for individual utility, it is possible to assign shadow costs to transport poverty. We define this shadow cost in terms of equivalent income changes, and thus the shadow cost of transport poverty is the amount of additional income needed to cancel out the negative effect of transport poverty on wellbeing.

We find that the shadow prices of transport poverty are high. For POV1 (i.e., if the share of public transport expenditure to income exceeds 10 per cent), on average, an individual requires $61,149 (71 per cent of annual household income) to offset the negative

Table 5
Robustness checks (Alternative Measures of Wellbeing and Transport Poverty).

	(1)	(2)	(3)
Panel A – DV is Life Satisfaction Dummy Using Welsch and Biermann cut-offs			
Transport Poverty	−0.127***	−0.031	−0.030*
	(0.038)	(0.021)	(0.018)
	[−0.055]	[−0.030]	[−0.033]
Observations	178,480	178,359	178,325
Panel B – DV is Life Satisfaction Dummy Using Mean Value as cut-off point			
Transport Poverty	−0.108***	−0.057***	−0.081***
	(0.030)	(0.014)	(0.016)
	[−0.025]	[−0.029]	[−0.011]
Observations	178,480	178,359	178,325
Panel C – DV is MHI-5 Mental Health Scale			
Transport Poverty	−0.714*	−0.360***	−0.423***
	(0.408)	(0.086)	(0.151)
	[−0.004]	[−0.012]	[−0.006]
Observations	158,128	158,015	157,984
Panel D – DV is K10 Distress Scale			
Transport Poverty	1.160***	0.497***	−0.083
	(0.312)	(0.117)	(0.107)
	[0.017]	[0.018]	[−0.003]
Observations	67,330	67,283	67,266
Panel E – Transport share with life satisfaction as DV			
Transport Poverty	0.002	0.147***	0.071***
	(0.030)	(0.028)	(0.015)
	[0.001]	[0.032]	[0.028]
Quadratic term	−0.000	−0.026***	−0.004***
	(0.040)	(0.001)	(0.000)
	[−0.000]	[−0.019]	[−0.021]
Observations	178,480	178,359	178,325
Panel F – 15% cut-off with life satisfaction as DV			
Transport Poverty	−0.198***	−0.031***	−0.030***
	(0.015)	(0.007)	(0.007)
	[−0.035]	[−0.011]	[−0.010]
Observations	178,480	178,359	178,325
Panel G – Effects of accessibility poverty with life satisfaction as DV			
Transport Poverty	−0.162**	−0.103*	
	(0.070)	(0.058)	
	[−0.036]	[−0.017]	
Observations	8,233	12,964	

Notes: All regressions include the usual control variables.
Standard errors in parentheses.
Standardized coefficients in brackets.
* Denotes p-value < 0.1.
** Denotes p-value < 0.05.
*** Denotes p-value < 0.01.

effects of being in transport poverty. For POV2 (i.e., if the share of motor vehicle fuel expenditure to income exceeds 10 per cent), an average person requires $21,380 (25 per cent of annual household income) to offset the negative effects of transport poverty, while for POV3 (i.e., if the share of total household transport-related expenditure to income exceeds 10 per cent), on average, an individual requires $14,588 to offset the negative effects of transport poverty on wellbeing.

These figures can provide general guidance to policy makers as to the costs of addressing transport poverty. In the HILDA dataset, for 1.2 per cent of the sample, the share of public transport expenditure to income exceeds 10 per cent (see Table A2). Australia's population is approximately 25 million people, which suggests that 300,000 people in Australia experience POV1. From a policy perspective, our results suggest that the cost of alleviating POV1 is $1.8 billion or 1.4 per cent of Australia's GDP. In the HILDA dataset, for 5.9 per cent, the share of motor vehicle fuel expenditure to income exceeds 10 per cent (see Table A2). This figure suggests that 1.5 million people in Australia experience POV2. Our results indicate that the cost of alleviating POV2 would be $3.2 billion or 2.4 per cent of Australia's GDP.

5. Conclusion

We have examined the relationship between transport poverty and subjective wellbeing using a nationally representative longitudinal dataset for Australia. In our baseline results, we find a negative association between transport poverty and subjective wellbeing. This general conclusion is robust to a number of checks. When we account for endogeneity of transport poverty using external instruments, heteroskedasticity-based identification and PSM, we consistently find a causal relationship between transport poverty and subjective wellbeing with quite large effect sizes.

Increasingly it has been suggested that improving subjective wellbeing, rather than maximising economic growth or focusing on other conventional economic indicators, should be a primary policy aim (Diener, 2000, 2006; Kahn and Juster, 2002). The shadow costs of the different transport poverty measures can be used by policy-makers as a guide.

When the shadow cost is multiplied by an estimate of the number of people experiencing transport poverty, this provides an implied market value of the cost of transport poverty. In other areas of policy concern, shadow prices have been used by policy makers to derive estimates of the cost of public bads, such as crime and pollution. The advantage of such estimates is that they represent what people are implicitly willing to pay to not be the victim of crime, experience pollution or live in transport poverty, which has been shown to be an accurate measure of estimating people's preferences (van Hoorn, 2018). Importantly, the implied costs of transport poverty can be compared with the implied costs of other issues on which governments spend money, such as addressing unemployment. In this sense, what really matters is relativities. If actual government expenditure across policy areas bears no resemblance to the implied costs, this is a good reason to readjust spending priorities.

In the Australian context, a specific recommendation stemming from our results is to improve transport infrastructure and services, particularly those pertaining to the outer suburbs of the major cities (Armstrong et al., 2015; Currie et al., 2009, 2010; Currie and Stanley, 2007). We find that the subjective wellbeing of those living in transport poverty, defined in terms of spending more than 10% of income on motor vehicle fuel, in the outer suburbs is most adversely affected among those living in transport poverty. Australians are very car-reliant and so most of their transport poverty comes from motoring costs. People living in the suburbs, where housing is often much cheaper, face rather long and costly daily journeys by car to get to work, as well as to hospitals, shopping centres and leisure activities. There is also a paucity of other travel options in these areas (e.g. better rail options might help in these areas but many do not have stations or rail services are very slow). Ideally, Australian cities need to offer cheaper housing options nearer the centre of cities and to reduce urban sprawl into the periphery, but in the short term the only option maybe to reduce the cost of motoring for the worst off, maybe through fuel subsidies or reconsider fuel excise taxes (Lyons and Chaterjee, 2002), which are inherently regressive.[3] Again, the advantage of our analysis is that the implied market values suggested by the shadow costs provide an estimate of the cost of addressing transport poverty and allow policy makers to compare the cost with other policy needs.

One potential limitation of the study is the use of a single item indicator – overall life satisfaction – to measure subjective wellbeing. This said, such an indicator is typically used by both economists and psychologists when employing large nationally representative datasets and responses to overall life satisfaction have been found to have adequate reliability and validity (Diener et al., 1999). Moreover, in robustness checks, we find the results for overall life satisfaction to be consistent with composite measures of subjective wellbeing, such as the five-item Mental Health Inventory (MHI-5) scale, which is a subscale of the short form (SF-36) general health survey, and the Kessler Psychological Distress Scale (K10).

One avenue for future research is to examine the nuances of the relationship between transport poverty and subjective wellbeing in more detail. For example, studies could examine potential mediators of the relationship, such as social exclusion, with nationally representative longitudinal data. Currie et al. (2010) do test social exclusion as a mediator of transport poverty and subjective wellbeing, but they only had a small sample and used cross-sectional data for a single city. With such data one cannot control for individual fixed effects and it is very difficult to draw causal inferences which are important for designing policy.

More generally, less than a decade ago, it was stated that the relationship between transport and subjective wellbeing was largely "unexplored in travel behaviour research" (Ettema et al., 2010, p. 729). More recently, in a survey of the topic, De Vos et al. (2013) concluded that research on transport and subjective wellbeing is still in its infancy and that many of the multifarious links between transport and subjective wellbeing have not been examined. While this is starting to change for some aspects of travel, such as commuting time, other dimensions such as transport poverty have not been explored. Given the relatively large number of people living in transport poverty and its importance for subjective wellbeing documented in these initial findings, further research on transport poverty is essential to inform policy and help pinpoint the best way in which to improve subjective wellbeing.

Declarations of interest

None.

[3] In October 2018, an estimated 160,000 motorists in Australia participated in a 'National Fuel Strike', protesting against the price of petrol. The strike entailed the motorists pledging on social media not to fill-up over a two day period. The strike was organised by a retired music teacher who had to give up her job because she could not afford the cost of fuel to drive 500 km a week to teach isolated children. One of the main calls from the protesters was for the government to reduce the fuel excise tax (Brook and Hevesi, 2018).

Appendix A

See Tables A1, A2 and Fig. A1.

Table A1
Mean wellbeing by transport poverty.

	POV1	POV2	POV3
Average wellbeing for respondents that are transport poor	7.432	7.761	7.695
Average wellbeing for respondents that are not transport poor	7.914	7.917	7.926

Table A2
Description and summary statistics of variables.

Variable	Descriptions	Mean	SD
Life satisfaction	All things considered, how satisfied are you with your life? On a scale of 0–10, where 0 is labelled as totally dissatisfied and 10 is totally satisfied	7.907	1.448
Mental health	Five-item Mental Health Inventory (MHI-5) scale	74.138	17.194
K10 Distress Scale	Kessler Psychological Distress Scale (K10)	15.805	6.388
POV1	Dummy variable equals 1 if share of household public transport expenditure to income exceeds 10%	0.012	0.106
POV2	Dummy variable equals 1 if share of household motor vehicle fuel expenditure to income exceeds 10%	0.059	0.236
POV3	Dummy variable equals 1 if share of total household transport-related expenditure to income exceeds 10%	0.079	0.270
Transport Share 1	Household public transport and taxis expenditure to income	0.012	0.378
Transport Share 2	Household motor vehicle fuel expenditure to income	0.044	0.319
Transport Share 3	Total household transport-related expenditure to income	0.057	0.564
ACCESS1	Dummy variable equals 1 if respondents had trouble getting a job because of transport problems or it was too far to travel	0.205	0.403
ACCESS2	Dummy variable equals 1 if respondents have not been looking for work because of lack of transport	0.018	0.131
Age	Age of respondent	44.327	18.640
Age squared	Square of age/100	23.124	17.933
Male	Dummy variable if respondent is male	0.474	0.499
Female	Dummy variable if respondent is female	0.526	0.499
Dependants	Number of dependents in household aged 0–24	0.608	1.034
Separated	Dummy variable if respondent is separated	0.026	0.160
Divorced	Dummy variable if respondent is divorced	0.061	0.239
Widowed	Dummy variable if respondent is widowed	0.048	0.213
Single	Dummy variable if respondent is single	0.241	0.4288
Married/De facto	Dummy variable if respondent is married or in a de facto relationship	0.624	0.484
Income	Log of household income	11.109	0.761
Employed	Dummy variable if respondent is employed	0.640	0.479
Unemployed	Dummy variable if respondent is unemployed	0.038	0.190
Not in Labour Force	Dummy variable if respondent is not in labour force	0.322	0.467
Postgrad	Dummy variable if respondent's highest education level achieved is masters or doctorate	0.043	0.204
Graduate Diploma	Dummy variable if respondent's highest education level achieved is graduate diploma or certificate	0.053	0.223
Bachelor	Dummy variable if respondent's highest education level achieved is bachelor or honours	0.134	0.341
Diploma	Dummy variable if respondent's highest education level achieved is advanced diploma or diploma	0.089	0.284
Certificate	Dummy variable if respondent's highest education level achieved is certificate I, II, III or IV	0.210	0.407
Year 12	Dummy variable if respondent's highest education level achieved is year 12 or below	0.471	0.465
Illness	Dummy variable if respondent is disabled or has a long-term illness	0.234	0.423
Oil stock index	NYSE Arca Oil Stock Price	1186.84	141.67
OPEC oil supply	OPEC oil supply (in millions of barrels)	37.194	1.095

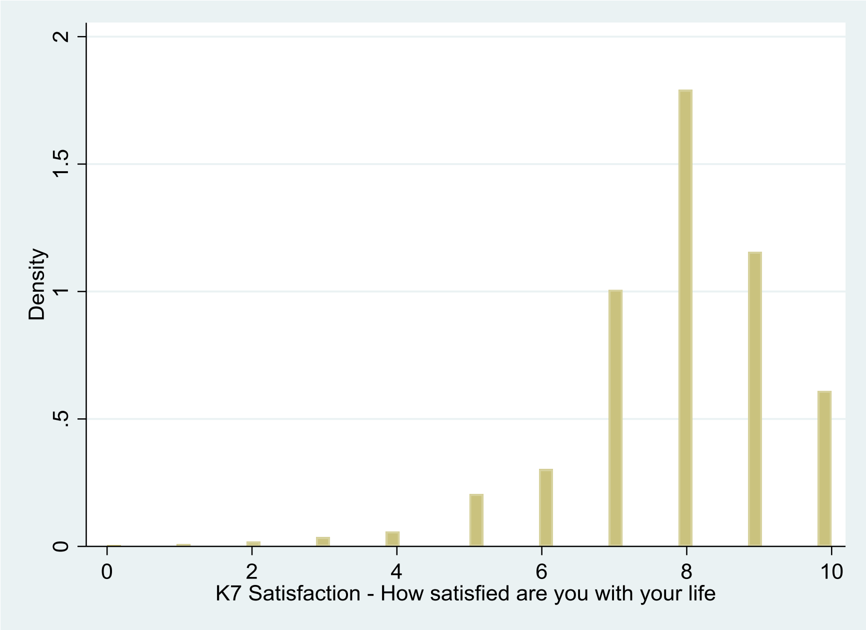

Fig. A1. Distribution of Life Satisfaction Response.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2019.03.004.

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