The demand for 'Active Travel': An unobserved components approach

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Abstract

This study informs the interface of travel demand analysis and health policy. There is a demand for cycling, walking or taking non-motorized modes together – a demand for 'active travel' - a term describing modes of transport which incur significant cardiovascular effort or metabolic costs. It is possible to establish a meaningful and policy relevant view of active travel demand by controlling for partially *unobservable* (not simply unobserved) generalized cost effects—where generalized cost can be considered the sum of all individual cost-components. Using monthly aggregated data from the UK National Travel Survey it is found that income effects are greater for lower income households and diminish with wealth and that some 'seasonal substitution', due to 'generalized' cost effects, can be identified. One consequence of this is that policy for active travel needs to be seasonally adaptive to reflect these substitution effects.

Key Words: unobservable components, 'active travel', 'seasonal substitution', seasonally adaptive policy.

1. Introduction

There is a significant existing literature pointing to the desirability and dimensions of non-motorized transport in the context of climate change and sustainable development (See, for example, Woodcock *et al*, 2009). Additionally, however, walking and cycling offer considerable health benefits (Sallis *et al*, 2004, Ogilvie *et al*, 2007, Pont *et al*, 2009), even though there are some limitations to the trip characteristics which they imbue, e.g. slower speed, shorter distance, nature of the built environment, limited carrying capacity, increased weather exposure etc. (See, for example, Nankervis, 1999, Saelens *et al,* 2003, Frank, 2004, Gatersleben and Appleton, 2007). The interface of transport and health policy uses the trope of 'active travel' to denote use of various travel modes requiring cardiovascular effort or substantial metabolic costs to be incurred.[1] For many trip purpose and journey length combinations it is possible to identify inverse 'U' shaped relationships between health outcome and cardiovascular effort (metabolic cost), insomuch as 'more' walking and cycling generally offers positive marginal health benefits when compared to no walking or cycling (see for example Hamilton et al., 2008), but as with any form of exercise excessive amounts of walking and cycling can inadvertently create health problems (see for example Lavie et al. (2015) who discuss the negative effects of both too little and too much exercise on the heart).

Transport strategy has recognized these benefits and evolved to accommodate the operational requirements of active modes of travel. The focus of this has been in terms of provision of cycling facilities, as facilities for walking are generally well tended to already (with the UK having an extensive network of footpaths nationwide). This is indirectly reflected in the UK Department for

[1] By 'active travel' we focus on cardiovascular effort (metabolic cost) proxied using travel distance expended in the service of getting from 'A' to 'B' – i.e. where the primary service is the journey itself. Thus running on a treadmill in a gym cannot be categorized as 'active travel'. We acknowledge that a number of authors in this area of the literature further distinguish between walking/cycling used for the separate purposes of recreation or as a main mode of transport, including Giles-Corti et al. (2005); Saelens & Handy (2008); Krizek et al. (2009); Sugiyama et al. (2012); Van Holle et al. (2012).

Transport (2015) Policy paper named ‘Setting the First Cycling and Walking Investment Strategy: setting the scene’ in which two probable strategic objectives are set forth (within section 3 of the document): (i) “To double cycling activity”; and (ii) “To invest over £200 million to make cycling safer…”, as yet no specific objective is tailored towards the unique needs of walkers – though admittedly there still remains a phase of government consultation before the objectives are finalised. Arguably the UK is one of the more progressive environments for the integration of active travel into formal transport strategy design,[2] as can be seen for instance in the joint UK Department of Health and Department for Transport “Active Travel Strategy” (2010), though other nations are implementing active travel related policy. In another example the Greek government (Ministry of Infrastructure, Transport and Networks, 2010) recently proposed a number of strategies to shift commuters from using private cars to public transport and bicycles including the provision of large scale bicycle routes – one within Athens (13 km) and a second connecting Athens’ city centre with the coast (8 km).

This study presents a means of analyzing active travel and the principal economic relationships that underlie its demand. In particular, the study indirectly measures the unobserved generalized cost of combined recreational and non-recreational cycling and walking thus treating them as a unified mode of transport referred to as ‘active travel’.[3] This is consistent with already widely applied operational planning principles. Hitherto, planning principles and academic literature treat policy and interventions for active-travel in a fairly linear way—prescribing broad policy instruments such as: provision of cycle parking; maintenance of active travel infrastructure; creation of cycle loan schemes; promotion of tourism, leisure and sport; integration with local

[2] We thank a referee for posing the question: How effective is the UK at implementing active travel policies? We simply do not have the evidence within the scope of the data considered for this study to provide an answer with a great deal of accuracy, but anecdotally if one were to consider the provision and use of cycling facilities in 2015 compared for instance against 2000, it would be fair to say that there are clear differences. Growth in the provision of cycle routes and city-wide cycle hire schemes also support this. To this end the UK may be considered effective, but whether it is as effective as it could be remains a reasonable separate question.
[3] Distinguishing it from the previous work of Broadstock and Collins (2010) for example, which focused on non-recreational cycling only.

public transport operators; reduced speed limits on surrounding road networks etc., see for example Sustrans and Transport Scotland (2014) for a representative example of policy guidance. This study however presents evidence of the need for seasonally adaptive policy instruments.

The scientific and societal value of this work derive from the following aspects: first is that it provides an initial inquiry into within-year trends in the consumption of walking and cycling, which among other things pays dividends in terms of revealing consistent seasonal substitution effects. It is subsequently argued that this finding creates room for devising seasonally adaptive policy instruments—something which has not featured strongly in existing policy discourse. Further it is highlighted (through the results reported in Section 3) that the nature of active travel as a good may vary with income, with implications of it being considered an inferior good at lower-mid levels of income; though for cycling specifically, there seems partial evidence of an additional status effect at higher income levels. Indirectly the research raises to the fore the fact that in certain cases, such as with the demand for active travel, existing national survey data makes it less than straightforward to providing robust and meaningful analysis that is capable of directly informing and evaluating existing policy objectives and the instruments used to achieve them.

2. Methodology and Data

This section presents and describes the data and methodology used in the analysis. There is no natural measure of cost/price for either walking or cycling (e.g. for car travel fuel cost would be one natural measure of price) however it is nonetheless implicit that consumers respond to some notion of cost. This is consistent with the familiar notion of generalized cost in transport which suggests that consumers respond to all measures that reflect the 'value' of a journey. For example, the cost of walking would increase with bad weather, unsafe streets or hilly environments requiring increased metabolic exertion. Moreover, policy design often hinges on the availability of cost information with tax policy being an obvious example, where taxes (or subsidies) are used to discourage (encourage) demand. With this in mind, the desire is to quantify the structure of a demand function for active travel and reveal some concept of net costs for active travel. The notion of cost that will be revealed is fully general, and in essence the *net* 'generalized cost' of travel. Unlike in some cross-sectional or panel based studies, the purpose of this study is not to identify individual cost components, rather to use statistics to reveal a net cost and more importantly the dynamics of this net cost. There is an obvious tradeoff in this approach where clarity of individual effects is sacrificed in favor of greater certainty of the net effect.

Specifically, the underlying net generalized cost information will be estimated as an unobserved component within a broadly defined demand function (defined at the national level) conditioned on observable income effects e.g.

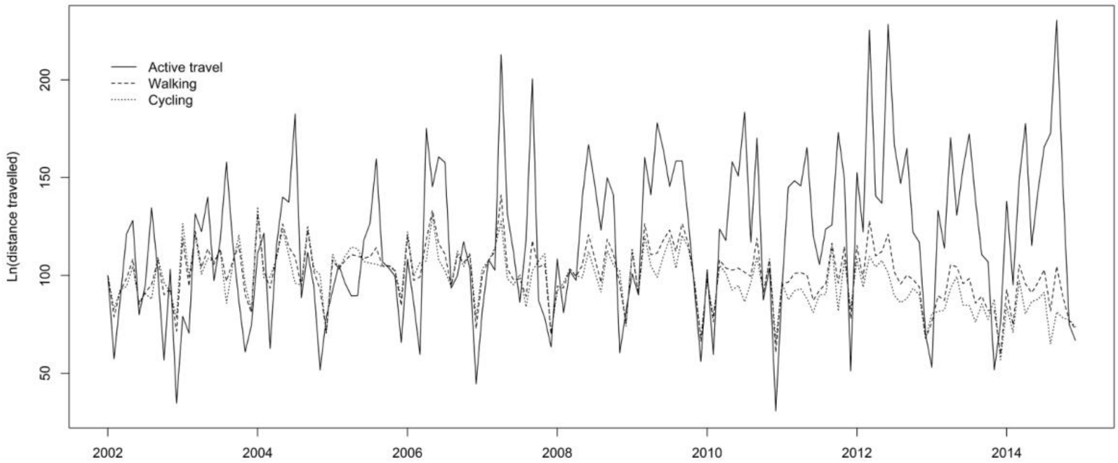
$$Q_d = f(\underbrace{g(C_1, C_2, ..., C_k)}_{\text{unobserved}}, Y) \tag{1}$$

Where Q_d is the quantity of active travel demanded, Y is some measure of income/wealth and $g(C_1, C_2, ..., C_k)$ is the net cost component which is acknowledged to be some aggregate reflection of a function $g(\cdot)$ of individual cost contributors $C_1, C_2, ..., C_k$. Admittedly some components of the generalized cost $g(C_1, C_2, ..., C_k)$ can be controlled for within the data, but certainly not all. Thus the problem becomes one of understanding demand patterns when some or all of the cost components are latent. The econometric approach to handle this issue will be formulated after outlining the more readily defined demand and income measures.

The data are taken from the UK National Travel Survey (NTS) for the years 2002-2014. The NTS is an extensive quasi-panel survey reported on an annual basis with data that is collected on a rolling basis throughout the year. The NTS data for `demand' are aggregated for each month (thus leading to a final dataset with 156 consecutive monthly observations running from 2002:1-

2014:12) by summing up across all individuals and are summarized in Figure 1, along with their general characteristics described in Table 1. Demand in this instance is measured as total distance travelled (NTS variable 'SD' or stage distance) for either walking or cycling or active travel (the sum of walking and cycling). Survey weights (NTS weight variable 'W2') are used as recommended within the 'NTS User Guidance' to control for non-response bias in the travel survey diary sample.

(Figure 1a)



(Figure 1b)

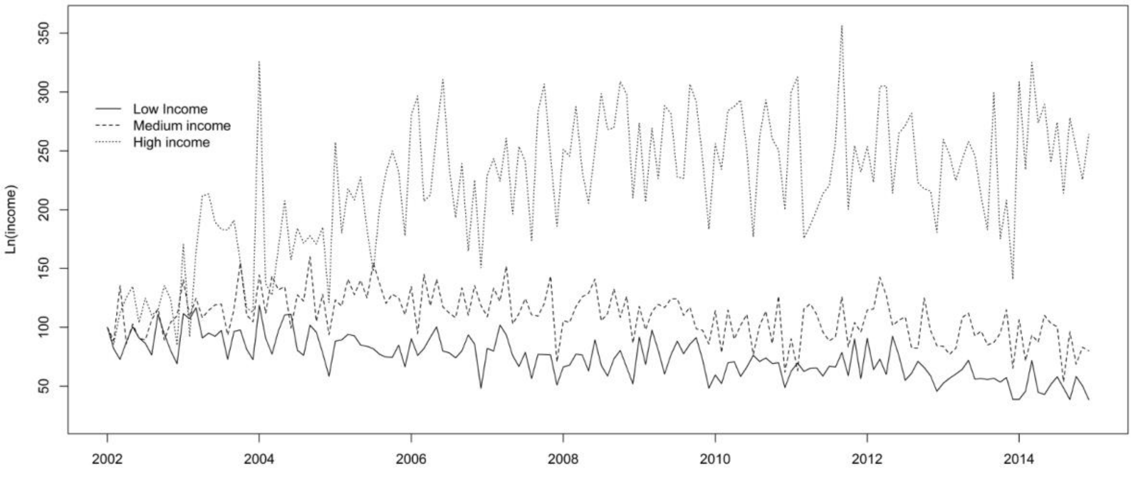


Figure 1: Estimation data: Demand for active travel measured in distance, indexed to 2002:1=100 (top panel, 1a) and Income measured in terms of the number of household types in each income group, again indexed to 2002:1=100 (bottom panel, 1b)

iable	Min	Mean	Median	Max	Average growth
Demand:					
Active travel	3.426	4.710	4.762	5.440	-0.002
Walking	4.091	4.601	4.655	4.949	-0.002
Cycling	4.042	4.569	4.592	4.906	-0.003
Income:					
Low	3.652	4.282	4.312	4.777	-0.006
Medium	3.986	4.678	4.704	5.075	-0.001
High	4.440	5.361	5.421	5.876	0.006

Table 1: Descriptive statistics for estimation variables. All variables are indexed to the base period 2002:1=100, then natural logarithms are taken.

In terms of a representative measure of income, the NTS does not provide for a well-defined and continuous measure of income making it necessary to use a proxy variable. Instead the NTS in recent years simply classifies a household as being either low, medium or high income. Income effects are therefore identified from the NTS survey data in terms of three individual series, the number of high income households $Y_{t,high}$, the number of medium income households $Y_{t,med}$ and the number of low income households $Y_{t,low}$ (each indexed to a base of 2002:1=100). This classification is not arbitrary as high income households have a much higher probability of being composed of individuals with high income, and low income households cannot contain high income individuals by definition. Hence, the collinearity between household wealth and individual wealth is considered to be sufficiently high to make it a reasonable proxy. The two panels of Figure 1 provide plots for the individual series, and it can be seen that the number of high income households in the country is growing faster relative to the number of low income households, but that the general number of medium income households remains largely stable. This figure also plots the demand index for active travel, which includes both walking and cycling. It should be recognized that the generated data, which might otherwise be referred to as pseudo-time series data, is reflective of the weighted achieved sample. An alternative might be to consider the average household demand for travel, noting that the limit of a sample mean tends to the population mean as the sample tends to infinity, thus making the mean an appealing alternative. However, the lack of definition in the income measure precludes this being a useful approach.

Alternative ways of constructing a plausible measure of income were considered, including for instance using the British Household Panel Survey (BHPS) data. However, BHPS data are not collected during summer months, thus this would result in a number of periodic missing data that would need to be imputed creating additional technical complications. Previous versions of the NTS, for example 1995-2001, recorded income in a different manner to the current sample. Specifically, individual incomes were recorded in the previous data, offering much greater ability to consider demand patterns/functions more explicitly, however in later years this variable was unfortunately dropped in favor of more general (in the sense of less specificity) measures of total household income.

With respect to econometric specification, methods have been developed to account for situations in which there are unobserved variables. For time series analysis, as done here, the structural time series model developed by Harvey (1989) is one such method.[4] The structural time series model is increasingly used in economic literature due to its general flexibility. Specified appropriately, through the use of a Kalman filter and a maximum likelihood estimator the model is able to explicitly control for unobserved components in a time-series model without consuming valuable degrees of freedom. For example Bijleveld *et al* (2008) use the method to evaluate the difference

[4]This model has been used before to look at interactions between transport and health related issues, see for example Harvey and Durbin (1986) who explored the impact of seat belt legislation on road traffic fatalities.

between actual latent risks and the best available measures. In the present paper there is a lack of available measures to help form parts of the price series and hence the entire aggregated effects are treated as a combined unobserved series. The model to be estimated is expressed (in a standard double-log form) as;

$$\ln Q_{dt} = g(C_1, C_2, ..., C_k) + \delta_1 \ln Y_{t,low} + \delta_2 \ln Y_{t,med} + \delta_3 \ln Y_{t,high} + \varepsilon_t \tag{2}$$

Where the unobserved net generalized cost effect is modeled as an unobserved component using a stochastic trend term so that;

$$g(C_1, C_2, ..., C_k) := \mu_t \tag{3}$$

$$\mu_t = \mu_{t-1} + \eta_t + \xi_t \tag{3a}$$

$$\eta_t = \eta_{t-1} + \zeta_t \tag{3b}$$

Where ':=' means equal by definition. Equations 3(a) and 3(b) are the 'transition' equations for the stochastic trend, more simply they state that the estimated unobserved component must be *systematic* as in any given period it is a function of itself in the previous period. Other unobserved information that does not follow some *systematic* pattern (for example an un-seasonally cold month) would not be captured in the stochastic trend, rather it would still appear as a standard outlying residual as in a standard regression. In this regard μ_t is considered a reasonable proxy for $g(C_1, C_2, ..., C_k)$ such that some form of generalized cost information, albeit aggregated, can be inferred from the model.

This specification is further augmented with additional terms to (i) control for longer term cyclical type effects (stretching over months or even years as determined by the estimated coefficients) and (ii) to allow for a stochastic seasonal trend to capture monthly adjustments in consumer demand.[5]

[5]The main differences between the stochastic seasonal and the stochastic cycle are twofold. Firstly, the stochastic seasonal is set to capture seasonality within the domain of a given year, whereas the cycle term may stretch over a part of a year or over multiple years. Secondly, the structure of the cycle term is such that it captures a smoother oscillatory motion, whereas the seasonal trend term is far more loosely defined, and hence not likely to be as smooth or evidently oscillatory.

Omission of any of these features will be determined on the basis of a combination of diagnostics checking and use of likelihood ratios tests for the validity of restricted versions of the model. The model can be re-specified as:

$$\ln Q_{dt} = \underbrace{\mu_t + \varphi_t + \psi_t}_{g(C_1, C_2, \ldots, C_k)} + \delta_1 \ln Y_{t,low} + \delta_2 \ln Y_{t,med} + \delta_3 \ln Y_{t,high} + \varepsilon_t \qquad (4)$$

$$\mu_t = \mu_{t-1} + \eta_t + \xi_t \qquad (4a)$$

$$\eta_t = \eta_{t-1} + \zeta_t \qquad (4b)$$

$$\text{Stochastic seasonal:} \quad \varphi_{1,t} = -\varphi_{1,t-1} - \varphi_{2,t-1} - \ldots - \varphi_{11,t-1} + \omega_t \qquad (4c)$$

$$\text{Stochastic cycle:} \quad \psi_t = \psi_0 \cos \lambda_c t + \psi_0 \sin \lambda_c t \qquad (4d)$$

Where $\varepsilon_{ti} \sim N(0, \sigma^2_\varepsilon)$, $\eta_{ti} \sim N(0, \sigma^2_\eta)$, $\zeta_t \sim NID(0, \sigma^2_\zeta)$ and $\omega_t \sim NID(0, \sigma^2_\omega)$, i.e. the disturbance terms are assumed to be Gaussian normal$\xi_{ti} \sim N(0, \sigma^2_\xi)$. These seasonality and stochastic cycle effects are assumed to be components of generalized cost insofar as they are clearly independent of income effects and therefore reflect other features that systematically influence consumers' valuation of active travel. For instance the seasonal will broadly reflect the effect of weather, where winter weather for instance will infer characteristics that consumers are less willing to expose themselves to such as wind and rain, and in turn this implies a higher perceived cost for travel during such periods.

There is a prominent area of literature focused on defining travel demand patterns as a function of activity, or journey purpose, see for example Bhat (2003). While in principle it is feasible, in practice there is considerable fuzziness in the responses of those surveyed. By way of example, consider a commuter who decides to travel to work by bicycle such that their stated purpose of travel is commuting. Their decision could be motivated not only by the need to get to work, but also by the ability to perhaps ride along a scenic cycle route , both avoiding heavy traffic while receiving ‘value’ from the beauty of the surroundings (perhaps also with cleaner air and greatly reduced noise pollution). Moreover though, the decision to travel by cycle might further be prompted by a desire to engage in regular cardiovascular activity, generally resulting in long term health gains. Hence, while the primary purpose of a trip may be easily revealed by the NTS, there remains no natural mechanism or prior means to readily identify the ‘true’ purpose *or* purposes of travel made using active modes of travel. While this in itself seems a fruitful research issue to be given further attention, it is neither within the feasible scope, or the focus of the present paper to discuss this issue further.

3. Results

The results from the estimation are summarized in Table 2, with all diagnostics checks (checks for misspecification problems) being satisfactorily passed. All models retain stochastic (or time-varying) seasonal and cycle effects, though the stochastic trend only remains within the walking model, being reduced to deterministic trends for cycling and combined active travel on the basis of likelihood ratio tests.

	Active travel	*Walking*	*Cycling*
Coefficient			
Low income	***0.324****	***0.401****	***0.041***
Medium income	***0.210****	***0.319****	***-0.165***
High income	***0.194****	***0.163****	***0.349****
Gasoline price			
Hyperparameters			
Irregular: σ_{ε}^2 x 10^{-5}	***0.000***	***0.000***	***0.000***
Level: σ_{η}^2 x 10^{-5}	-	***1.402***	-
Slope: σ_{ζ}^2 x 10^{-5}	-	-	-
Seasonal: $\sigma_{\psi 1}2$ x 10^{-5}	***0.000***	***0.000***	***0.000***
Cycle: $\sigma_{\psi 2}2$ x 10^{-5}	***0.000***	***0.000***	***0.000***
Cycle characteristics			
Cycle length in years	***0.35***	***0.42***	***0.48***
Frequency of cycle	***1.49***	***1.24***	***1.09***
Residual diagnostics			
Normality []	***0.64***	***0.03***	***3.88***
$H_{(48)}$	***1.74***	***0.96***	***1.22***
$r_{(1)}$	***0.03***	***-0.00***	***-0.10***

r(11)	***-0.02***	***0.08***	***-0.12***
DW	***1.90***	***1.95***	***2.16***
Q	***Pass***	***Pass***	***Pass***
R_d^2	***0.79***	***0.93***	***0.53***

Notes for Table 1:

(i) ****, ** and * represent statistically significant at the 1%, 5% and 10% levels respectively.*

(ii) *Normality is tested via the Bowman-Shenton statistic, approximately distributed as* $\chi^2_{(2)}$ *=5.991*

(iii) *H(n) is the test for heteroscedasticity, approximately distributed as F(n,n).*

(iv) *r(1) and r(10) are the serial correlation coefficients for lags 1 and 10 respectively, approximately distributed as N(0,1/T).*

(v) *DW is the Durbin Watson statistic.*

(vi) ***Q*** *is the Box-Ljung test for serial correlation. The degrees of freedom for this test vary by specification owing to the automatic lag-length choices in STAMP 6.3 – hence here it is only recorded as to whether or not the tests are passed, to simplify the exposition.*

Table 2: Estimation Results (2002:1-2014:12)

The first point to note is that across each of the three models the goodness of fit is generally high, implying that the combination of structural time components and income measures used to describe the characteristics of demand are reasonable. Cycling has the lowest R^2 at roughly 53%, but walking is very well explained at about 93% and active travel is also well explained at about 83%; serial correlation and heteroskedasticity tests are passed for all models. In terms of the specific components of the models, they are each discussed in turn starting with the elements of the 'cost' series, then moving to discussion of the income measures, and lastly concluding with an illustration of the empirical contribution of cost changes towards changes in the demand for active travel.

3.1 Net generalized cost analysis

The estimated combined cost series are summarized in Figure 2. Each of the series are generally very stable over time (implying mean-stationary processes), tending to revert back towards a stable level—albeit with some interesting deviations and dynamics about the common level. This implies that the underlying costs of active modes of travel have not materially changed over the sample period. This is perhaps not overly surprising given that active modes of travel do not have variable costs that are subject to strong market effects, such as for instance would be the case with the variable cost of gasoline used to run an automobile. The costs of cycling demonstrate a stronger seasonal variation than seen for waling, clearly resonating the importance in seasonal weather dynamics/length of daylight hours etc. on the degree of expense faced by cyclists throughout the course of a year.

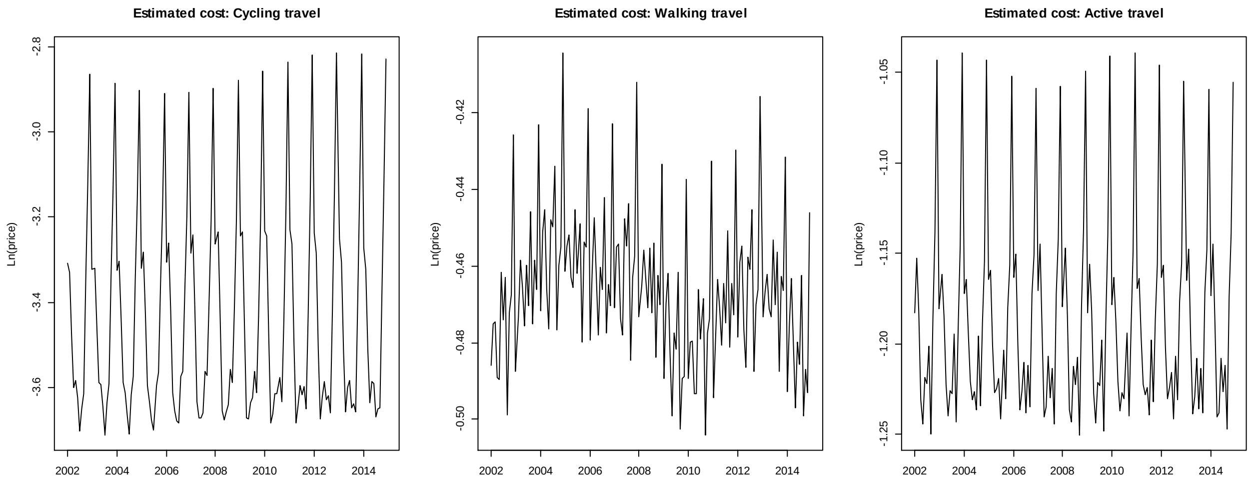


Figure 2: Derived price series from estimated equations (2002:1-2014:12)

As might be intuitively expected, the cost series for active travel seems to retain the properties of an average of the two separate modes of travel, clearly capturing the peaks and troughs seen in the cost of walking around the 2008:2009 period (discussed further in Section 3.1.1 below), but also exhibiting the more pronounced seasonal patterns seen in the cycling cost series. This is an intuitive and confirmatory finding insofar as active travel includes the combination of walking and cycling, and reflects the benefits and costs of each mode.

3.1.1 Stochastic trend

Turning to the individual components of the cost series, the estimated trend, cycle and seasonal effects from the econometric models are presented in Figure 3.

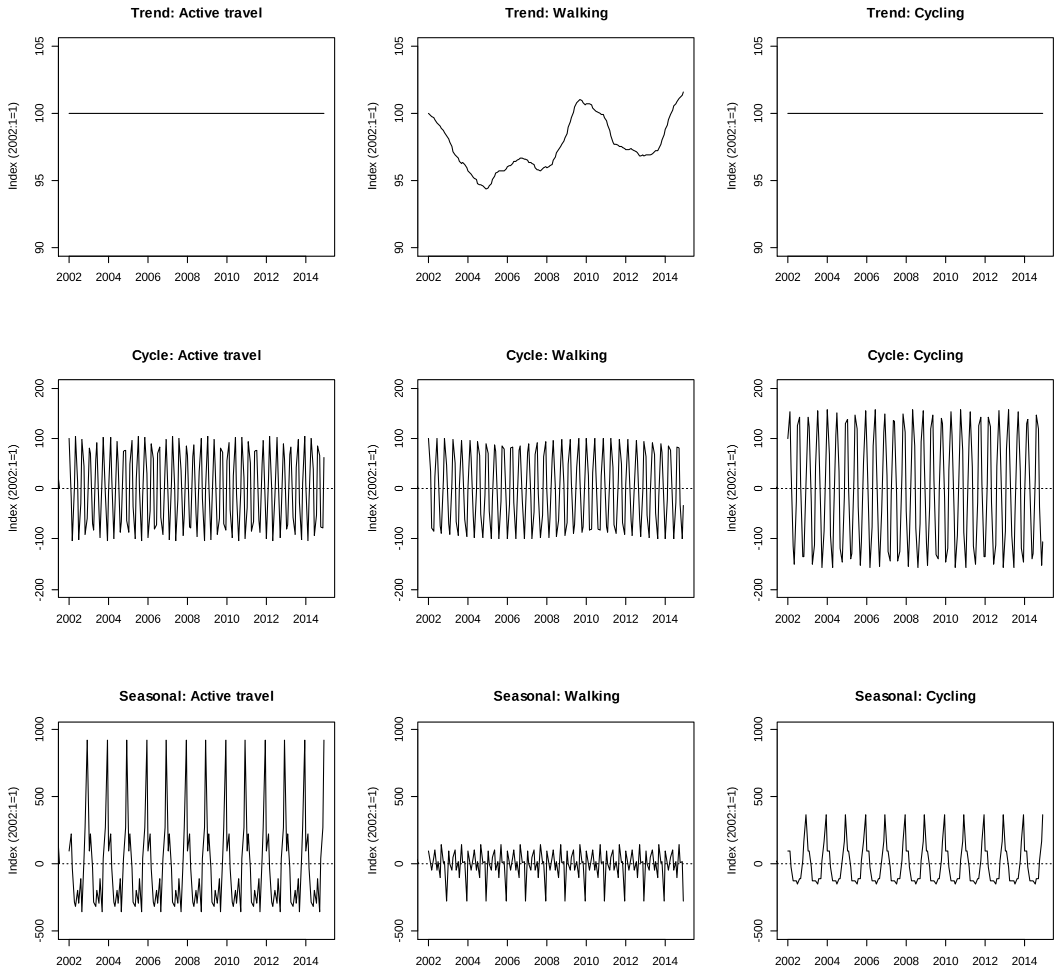


Figure 3: Trend, cycle and seasonal effects (2002:1-2008:12)

While the estimated models allow for an almost infinitely complex type of trend to be accurately estimated, the analysis reveals almost no role for a stochastic trend function when explaining this data. Rather, for two out of the three models (cycling and combined active travel), a deterministic trend is suggested. However when modeling the demand for walking, it alternatively turns out to be the case that a time-varying trend has a significant presence. The nature of the estimated trend displays some noteworthy patterns, not least of all the fact that in the lead up to the 2008 financial crisis there was a declining trend for walking, but during 2008 this trend was strikingly reversed leading to a relative surge in the demand for walking. Perhaps the reduced pace of economic activity created more time for individuals to engage in more walking. This trend is again shifted towards the end of 2009 back towards a pattern of declining demand for walking, which incidentally coincides with the timing of the UK emergence from the recession.

3.1.2 Stochastic cycle

The cycle components of the models highlight some subtle but interesting features. Firstly, from Figure 2 it can be seen that the model for active travel has the same form of trend as the model for cycling (which is in the end a deterministic trend as discussed previously), yet in terms of the stochastic cycle effects, the estimated cycle for active travel now appears to be more similar to cycling, at least in terms of the frequency of oscillation. Hence the model for active travel is not seemingly biased in favor of one model over another, rather it is mixing and matching the elements of the model which are most appropriate—a pattern which manifests also in the estimated coefficients, as will be highlighted further below.

3.1.3 Stochastic seasonal

Arguably the most interesting aspect of the estimated stochastic components of the cost series is in terms of the seasonal effects. Broadly speaking, the months which demonstrate increases in demand are those during spring and summer, with decreased demand during autumn and winter. The dip in June is potentially motivated by a combination of the academic and vacation calendars but this conjecture has only the status of informed speculation. For cycling the annual peak is in July, which is synonymous with increased domestic vacations in this month and in addition the school and college vacations such that households can generally travel more together and take advantage of the generally better weather.

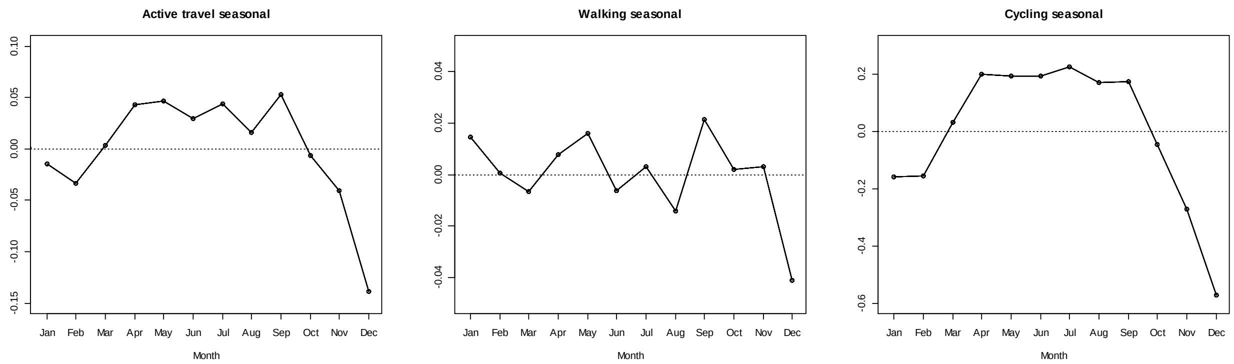


Figure 4: Estimated monthly seasonal trends (individual years overlaid)

Figure 4 plots the seasonal effects for the three separate models, with individual years overlaid on top of each other, while Figure 5 plots the first differences in the estimated seasonals for a representative year, noting that the same seasonal variation is observed for all years. The purpose of taking the first differences is to see whether or not each of the series move in the same direction (their co-movement) and therefore to imply whether they are consumed together (suggesting complementarity) or in place of each other (suggesting substitutability). The plot shows that walking and cycling are essentially complements for a large portion of the year, where they 'co-move', but for a number of months of the patterns of co-movement weaken. For instance in January (possibly as a reaction to Christmas time excesses) there is a marked strong positive increase for both walking and cycling, a pattern also seen in the months of April, July and September. For other months there are common decreases, such as August, October and December. Perhaps most interesting though are the months February, March, June. This reveals the presence of a measure of seasonal substitution. Both modes of travel reflect a period of exuberance in January, which is a useful indicator that UK citizens are willing to walk and cycle even in more adverse weather conditions—with January not providing the optimal balance of weather conditions for outdoor activity—when provided with suitable balance of behavioral motivations such as Christmas excess and the probable new-year resolution it may lead to. Worded differently, the fact that the largest increase in demand occurs within the winter is a strong indicator that increases in the demand for active travel can be propagated throughout the year.

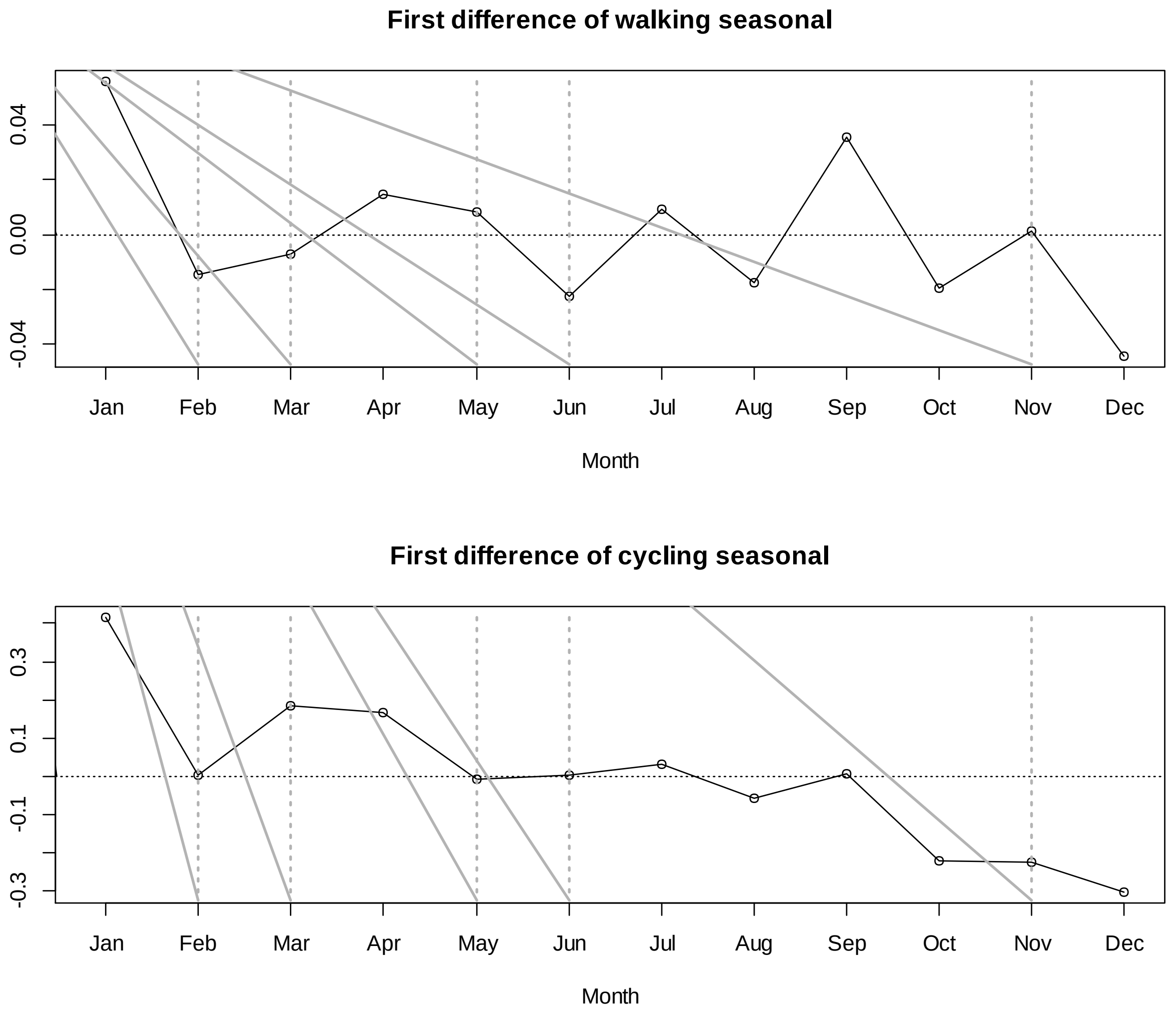


Figure 5: First difference of seasonal for walking and cycling

3.1 Income analysis

With regards to income and its effects on the demand for cycling, it is found that for medium and low income brackets, demand is income inelastic, while there is a significant elasticity within the high income bracket. This finding is broadly confirmatory of the findings given by Broadstock and Collins (2010) who contended that cycling resembles the potential characteristics of an inferior good insofar as demand for cycling is not increasing in income especially at lower incomes levels. Broadstock and Collins (2010) do however also raise the possibility that cycling may potentially be regarded as a status good within upper income brackets e.g. that its nature as a product depends at the reference point e.g. rich or poor, that it is perceived from. Turning then to the results in this paper, it is not possible to confirm cycling as a normal good given the low-medium income categories, while evidence of a positive elasticity with respect to higher income households creates room for the idea that suggested possibility that cycling may in part be consumed out of needs (or norms) for status.

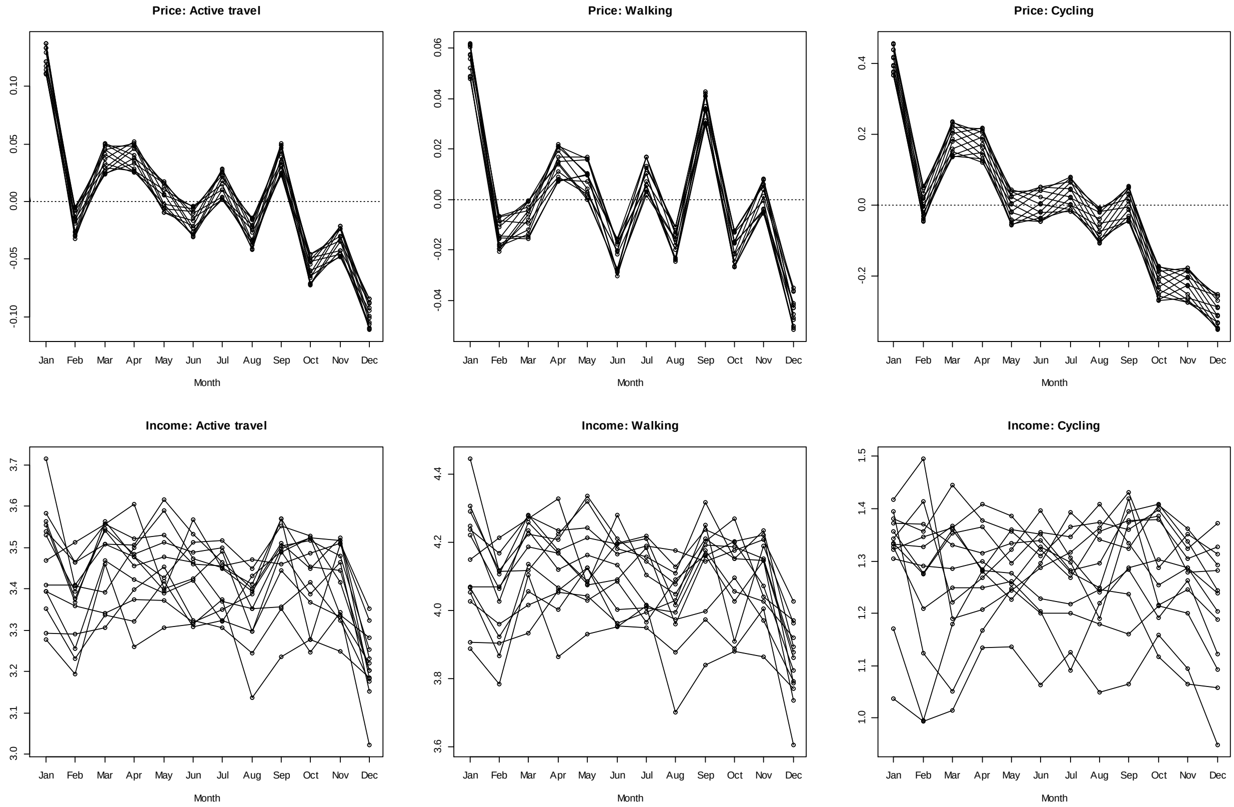
With respect to the models for walking and combined active travel, diminishing income elasticity is found, implying again that for higher income groups, the value of the income elasticity tends in the *direction* of an inferior good. The estimated coefficients in the active travel model are similar to those given by the model for walking. As with the case if the cycling model, it would however be too strong to claim inferiority as a conclusion. Nonetheless there is no doubting the conclusion that the income response is larger in the lower income households than the medium or higher income households.

Contribution analysis

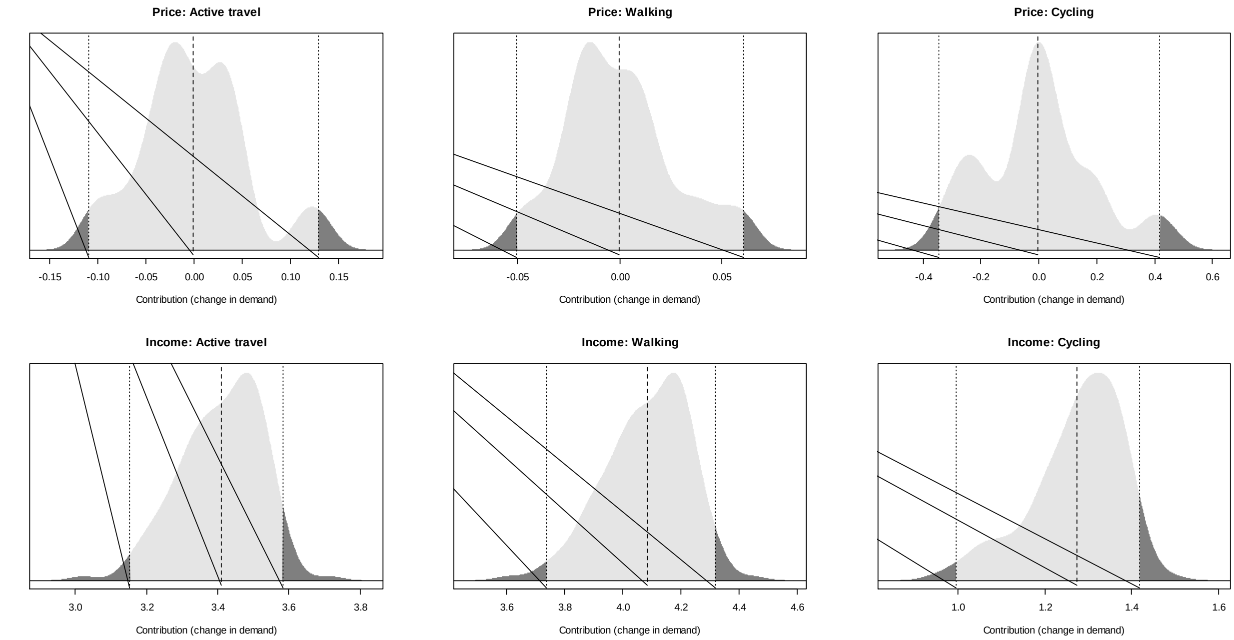
Given the estimated models the contributions of the net generalized cost effect and income towards changes in demand are evaluated using the following relationship, noting that by using the fitted values of demand the error term is eliminated.

$$\Delta\hat{Q}_{dt} = \underbrace{\Delta\hat{\mu}_t + \Delta\hat{\psi}_t + \Delta\hat{\varphi}_t}_{\text{generalized cost}} + \underbrace{\hat{\beta}_{low}\Delta Y_{t,low} + \hat{\beta}_{med}\Delta Y_{t,med} + \hat{\beta}_{high}\Delta Y_{t,high}}_{\text{income}} \tag{8}$$

Where Δ is the first order backwards difference operator such that $\Delta\hat{Q}_{dt} = \hat{Q}_{dt} - \hat{Q}_{dt-1}$.



(Figure 6a)



(Figure 6b)

Figure 6: Derived contributions of price and income indicators to changes in demand (2002:1-2014:12). Seasonal contributions (top panel, 6a) and empirical distribution of contributions (bottom panel, 6b)

The calculated empirical contributions are given in Figure 6, which provides overlaid seasonal plots for both cost and income in the top panel, and also their empirical distributions evaluated using a kernel density. This figure effectively highlights that the contributions of costs are heavily determined by largely systematic seasonal fluctuations (see top panel), but that during the course of a year these tend to zero (the means of the empirical distributions are given in the bottom panel). The contributions of income are less obvious in the seasonal plots of Figure 5 (top panel) but are clearer from the EDF's given in the bottom panel. The contribution of income is clearly positive for all models, though smaller for cycling than for walking or combined active travel.

Seasonal substitution and seasonally adaptive policy for active travel

Cumulatively the results demonstrate evidence of systematic seasonal substitution between walking and cycling, the two constituent modes of active travel. The evidence implies complementarity for the majority of the year, but with prominent substitutability at certain times of the year. In its current guise active travel is generally fostered on the trope of health benefits, which are generally less seasonal (i.e. it cannot be argued that any given month/season of the year is 'better' to be healthy than any other), though it is acknowledged that there are plausible environmental benefits also. However, recognizing that active travel is a policy solution and not a policy goal, then the evidence provided implies that policies aiming to encourage active travel should take into consideration the observed seasonal substitution. It is not entirely obvious how this can be utilized to immediate effect in policy design or implementation, nor is it the purpose of this paper to make specific policy conclusions/recommendations. Nonetheless it may for instance indicate support for increased investment in cycle hire schemes insofar as for certain months of the year (but not the whole year) there is a greater chance that individuals will substitute walking trips for trips made by cycle.

The analysis offered is based on a combined sample of individuals and makes no distinction between individuals that have an expressed preference towards active type modes of travel and those that do not. Neither does the analysis condition on cycle ownership levels. This would be an interesting avenue for future research however data limitations continue to apply. For instance if considering cycle ownership it might be of interest to control for average cycle purchase prices, however in the UK Family expenditure survey no such category exists thus precluding this possibility. Furthermore, decomposing preferences for active travel from other types of travel—which will include for instance sustainable travel—is likely to be far from straightforward, not least of all because measures such as body mass, which might imply a preference/need for active travel are not recorded in the NTS data. This further raises question over the ability of the NTS survey data to inform planners in respect of stated policy objectives e.g. to encourage active travel partly due to health benefits. However such questions are similarly far from easy to tackle. Nonetheless it is an interesting feature of UK national survey data that health surveys contain limited information on physically active travel, transport surveys contain limited health information, and expenditure surveys do not include key consumption items used in national level policy. It is duly recognized that surveys are undertaken for specific purposes and that individual questions are *not* costless when surveying thousands of households, thus budget constraints inescapably impact the structure and specificity of information in any given survey. Nonetheless, forming a consistent perspective on certain policy relevant topics in such instances inevitably results in empirical generalizations as utilized in this paper, e.g. a proxy for income and no distinction between pure-money and non-money costs in the generalized net cost approximation.

4. Discussion and Concluding Remarks

The operational requirements of transport networks are evolving to accommodate the increasingly important benefits found in active travel. Leading to improved health outcomes as well as contributing to sustainable development targets, active travel is increasingly appealing. Urban planners and transport practitioners have already begun to reflect this in their work, and strategy is also evolving to reflect this more directly.

With a view to further supporting the uptake of active travel, it is contended that there is value in treating combined walking and cycling as a unified mode of transport. The unobserved components approach provides no attempt to describe the individual elements of generalized cost, but should nonetheless produce an accurate reflection of the net-cost effect. The method applied has the distinct advantage of not only being able to quantify some unobserved component, but also to systematically decompose the unobserved component into specific factors relating to trend, cycle and seasonal effects. The latter of these points proves in some ways to be the most interesting arising from this study, implying an interesting element of seasonal substitutability that could have important ramifications for effective policy design.

The concept of seasonal substitution is a particularly under-researched phenomenon in transportation and many other policy domains. The idea that substitution may be lesser or greater throughout the year (or even, as in the present case, periodically change to complementarity) is something that can potentially be harnessed to support the regulation of market activity more effectively. The development and delivery of mainstream policy instruments is often carried out in a time-homogenous fashion, i.e. where no account is given of months or seasons, and how they may enhance or detract from the effectiveness of any given instrument. Although in many ways an intuitive and obvious observation, the results in this study categorically and systematically demonstrate the potential for seasonally adaptive policy instruments for active travel.

This study is not without its limitations and some of these must be openly conceded. For example the evidence of seasonal substitution might give rise to a more complicated demand function than this study allows for, and future research should consider this possibility. Specifically, system demand models are a natural way to consider substitution effects.[6] In addition, the study has deliberately sought to focus on a nationally representative measure of demand, but to adapt the analytical methods for use with household and/or individual level survey data would seem to be both a natural and important extension.

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[6] However estimating system demand with unobserved prices would intuitively seem complicated owing to the need to attach coefficients to unobserved price components in order to derive substitution elasticities. Multi-stage estimation procedures may possibly help here.

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