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EFFECTS OF TIMETABLE RELATED SERVICE QUALITY ON RAIL DEMAND

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Abstract

This paper is concerned with the suitability of and component weightings within the composite index Generalised Journey Time (GJT). GJT is used to model rail demand in Britain and is composed of station-to-station journey time, service headway and a penalty for the need to change trains. We analyse a large data set of rail ticket sales data to explore three features of GJT. The first is to determine how GJT impacts on rail demand, including interactions with distance and value for money and exploring the effects of the size and sign of the change in GJT, distinguishing between short run and long run effects. The new evidence obtained was important given concerns over the elasticities previously recommended for use in the rail industry in Britain. Secondly, we provide evidence as to whether the weights associated with headway and interchange in GJT are appropriate. Our analysis indicates that more influence should be attached to interchange. Finally, the rail industry in Britain's approach of using GJT and fare is quite unique. We have tested how it compares with the more traditional approach of generalised cost and with the specification of separate elasticities to the component parts of GJT. This indicates that the GJT approach is preferable to the more conventional approach although there would seem to be value in further pursuing separate elasticities to the components of GJT.

1. INTRODUCTION

Generalised Journey Time (GJT) is a concept unique to the railway industry in Britain and from the earliest forecasting applications in the 1970s it has been used as a means to represent the overall timetable related service quality of a train service. GJT is made up of: station-to-station journey time, including any time involved in interchange[1]; a frequency penalty, reflecting the inconvenience of not being able to travel at the desired time; and a penalty for each change of train during the course of a journey. Its background stemmed from an identified need to be able to represent overall attractiveness across diverse train services with, say, a mix of limited through services, connecting services of varying speeds and numbers of required connections, and highly irregular service intervals. Whilst service patterns are now generally much more homogenous across journey time, interchange, and departure times, GJT remains an important representative measure.

The rail industry in Britain has long adopted an apparently unique practice of using separate fare and GJT terms in forecasting demand as set out in its Passenger Demand Forecasting Handbook (PDFH). The latter document (ATOC, 2013), first introduced in 1986, is perhaps unique amongst rail organisations worldwide in recommending a comprehensive forecasting framework and associated demand parameters based on a distillation of best available evidence to provide a consistent basis for strategic business planning and the appraisal of important pricing and investment decisions.

The purpose of this paper is to investigate the functional form and weight estimates for GJT using sales data for non-season tickets and for station-to-station movements not involving London. We build an econometric panel data error correction model and divide our analysis into three parts.

- First, we examine the GJT elasticity in somewhat more detail than is customary, examining whether the response to changes in GJT differs depending on the size and sign of the GJT change and if the response is a function of trip distance and value for money of travel (in terms of fare).
- Second, we consider whether the current formulation of GJT specifies the appropriate weights by estimating a model with freely varying weights.
- Third, we consider whether it is better to dispense with the GJT concept and either replace it with separate components (no index function) or alternatively add GJT to fare via some exogenous or endogenous weight to form a Generalised Cost model.

Therefore this paper is concerned with how timetable related service quality - namely journey time, frequency and interchange - impact on rail demand, in terms of the extent that the current index function, GJT, is appropriate. It does not consider the influence on demand of other service attributes, such as crowding, rolling stock and travel time reliability, as these enter outside of GJT index. Whilst the results are derived for GJT in the British context, there is wider applicability to the use of indices, the most common of which is generalised cost, that are widely used in transport planning practice.

[1] Unlike standard transport planning practice, this connection time does not have some premium weighting but is treated the same as on-train time, and this can be seen as a shortcoming of the approach. The reason for this is historic; in the early years of application, distinguishing connection time from station-to-station time was not feasible in the computer models dealing with a large number of flows offering very diverse service patterns.

The structure of this paper is as follows. Following this introduction, Section 2 details the railway context of GJT (2.1), previous research into the elasticity associated with GJT and the weights comprising it (2.2) and new research needs to which this paper addresses (2.3). Sections 3 and 4 outlines the data and methodology respectively for our study. Section 5 discusses the results and section 6 concludes.

2. BACKGROUND

2.1 Generalised Journey Time in the British rail sector

GJT stemmed from the need for an index to represent the timetable related attractiveness of train services which have somewhat different journey times, departure time profiles and interchange requirements across the day (Tyler and Hassard, 1973). Ultimately this paper is concerned with whether this is a reasonable index method and if there are indices (either in terms of GJT or generalised cost) which better capture service heterogeneity.

The demand function in rail (and other) direct demand models is typically specified in constant elasticity. It takes the form:

$$V = \mu GJT^{\lambda} F^{\gamma} GVA^{\delta} \tag{1}$$

where λ is the GJT elasticity, γ is the elasticity to fare (F), δ is the elasticity to income (GVA) and μ represents all other factors that determine the number of rail trips, which in turn could comprise a set of further covariates, such as price of other modes. GJT is constituted as:

$$GJT = T + \alpha H + \beta I \tag{2}$$

T is the station-to-station journey time, including any interchange connection time. The frequency penalty (α) and interchange penalty (β) convert service headway (H) and the number of interchanges (I) into equivalent journey time[2].

By way of background, the frequency penalty covers a mix of random arrivals at the station when service frequencies are higher, whereupon wait time is the relevant measure, and planned arrivals and hence displacement time values at lower service frequencies. So using a value of wait time that is twice in-vehicle time, as is customary, the frequency penalty is equal to one at higher service frequencies where wait time is half the service interval. A value of displacement time of either 0.2 or 0.4 is used for planned arrivals, depending upon journey purpose, along with a ‘planning penalty’ of 15 minutes. So for a 30 minute headway, the frequency penalty is in the range 0.70 to 0.90 and for an hourly service it is in the range 0.45 to 0.65.

The interchange penalties used in PDFH are unlike those typically used in transport planning which tend to be of the order of a few minutes to reflect the pure inconvenience and risk related aspects of interchange independent of any connection time. In PDFH, and for historic reasons, connection time has not been separated from station-to-station time. Given that connection time is regarded to have a premium valuation, the interchange penalty used therefore proxies for the unweighted connection time. In addition, there is an allowance for

[2] Note that for convenience we here represent the frequency and interchange penalties as constants when in PDFH the former are a function of the service interval and ticket type and the latter are a function of distance and ticket type.

distance, justified on the grounds that otherwise the effect of a fixed interchange penalty within GJT is too small for longer distance journeys. By way of illustration, and for non-season tickets, the recommended interchange penalties for 30, 100 and 200 mile journeys are respectively 19, 40 and 65 minutes.

Whilst GJT could be enhanced with other time related terms, the inclusion of variables such as access to and from trains, crowding, rolling stock and travel time reliability in time-series models based on station-to-station movements is fraught with difficulty, for reasons such as limited variation over time, the absence of historical evidence, the lack of suitable detail and the difficulty of measurement. PDFH recommendations do though recognise that changes in GJT take time to have their full impact on demand.

The usual estimation procedure is to take the best evidence relating to α and β to construct GJT and then estimate λ by regression of V on GJT and other relevant terms. An exception is Wardman and Whelan (2004) who simultaneously estimated λ, α and β.

The GJT approach implies elasticities to the component parts of GJT, forcing the elasticities to time, headway and interchange to depend upon the proportion that each forms of GJT on a particular flow. These elasticities (η) are:

$$\eta_T = \lambda \frac{T}{GJT} \tag{3}$$

$$\eta_H = \lambda \frac{\alpha H}{GJT} \tag{4}$$

$$\eta_I = \lambda \frac{\beta I}{GJT} \tag{5}$$

Thus whilst the elasticity to GJT is constant, in contrast the implied elasticities to time (η_T), headway (η_H) and interchange (η_I) will vary strongly across routes depending upon the mix of T, H and I and the α and β relevant to each route. So the benefits of, say, improved frequency will be greater on services which are fast and direct but currently infrequent, which has an inherent reasonableness to it.

Overall the concept of GJT is useful in that it provides a single index which is parsimonious and thus easy to use for forecasting purposes. However an inevitable trade-off here is that the adopted index function may be too inflexible to accommodate the richness in demand response to service quality attributes i.e. the functional form of the index may be too simplistic. Secondly, conditional on the form of the index function, the weights within it need to be estimated. Clearly the precision of these estimates will be of importance in order to provide robust demand forecasts.

2.2 Previous Research

There has been a wealth of research into GJT elasticities in Great Britain, facilitated by the availability of ticket sales data over many years that records the number of trips between stations with corresponding evidence on, amongst other things, station-to-station GJT.

Wardman (2012) reports an extensive review and meta-analysis of time based elasticity evidence based upon this wealth of evidence in Great Britain. It covered 427 time based elasticities, including 209 GJT elasticities (all of which were specific to rail), 168 time elasticities and 50 headway elasticities. A model was developed to explain variation in elasticities across studies, finding the GJT elasticity to increase with distance, to be lower on Non London inter-urban flows and to differ considerably by data type and between the short and long run.

The meta-analysis indicated a long run GJT elasticity for Non London movements of -1.10 for 50 mile journeys and -1.45 for 100 mile journeys, ,which are typical of the sorts of trips here examined, and implied a long run elasticity some 3.5 times the short run (4 week) elasticity.

In contrast, PDFH then recommended GJT elasticities between -0.70 and -1.10 for inter-urban travel (ATOC, 2009), with some ambiguity as to their temporal status. As a result of this meta-analysis, the most recent version of PDFH (ATOC, 2013) adopted an explicit long run GJT elasticity for Non-London inter-urban flows of -1.2.

As this meta-analysis reveals there have been many studies that have provided evidence on GJT elasticities in the British context. However, we can make three important comments in the light of this evidence base:

- Outside of Great Britain, there is little econometric analysis of how rail demand varies with changes in timetable related service quality simply because there is insufficient reliable data to support such analysis.
- Even though there have been many econometric studies of ticket sales data in Britain that have returned robust elasticities to timetable related service quality in the form of GJT, very few of these studies have gone beyond estimating a constant GJT elasticity.
- Discrete choice models provide an alternative strand of work yielding time elasticities, with a particular interest in forecasting the impact of high speed rail and new rail-based rapid transit systems.

As far as econometric analysis of actual rail demand changes is concerned, which is the focus of this paper, our understanding is that the first detailed examination of timetable related service quality was reported by Wardman (1994). It estimated separate elasticities to the components of GJT, and explored whether these elasticities depended upon the level they took and distance, and also tested whether the elasticity variation implied by equations 3-5 above could actually be empirically justified.

Ten years later, Wardman and Whelan (2004) built upon this work in part to provide updated GJT elasticities but also to examine a range of other issues. A novel aspect was that they estimated directly the frequency and interchange weights within GJT as well the GJT elasticity itself, but the results were ‘mixed’ and were never adopted by the rail industry in Great Britain in terms of amended recommendations in PDFH. They also reported comparisons of the rail industry approach of separate GJT and fare elasticities with the standard transport planning practice of combining the two into a single Generalised Cost term. The evidence supported the rail industry approach over conventional transport planning practice.

There have been many mode choice based studies of the potential for new rail-based rapid transit systems and high speed rail services which yield elasticities to the service quality variables of interest here. Much of this evidence is unpublished, although the meta-analysis reported above covered such UK studies, and it is beyond the scope of this paper to provide a comprehensive account of all studies in these areas.

2.3 The Need for Further Research

The research need we here identify is related to changes in the service quality of conventional train services. High speed trains tend to serve different markets and certainly deal with much larger time savings. At the other extreme, studies of rail-based rapid transit services, whether metro or tram, relate to markets where trip length is generally short and competition from other modes is intense.

Given we are interested in the markets that the British railway industry's unique PDFH seeks to address and in particular the longer distance services, further detailed econometric analysis of ticket sales data to determine how changes in timetable related service quality impact on rail demand is warranted for the following reasons:

- The very first edition of PDFH in 1986 stated "PDFH attempts to bring together all the sources of evidence on the responsiveness of passenger demand for rail travel to changes in a large number of attributes. It provides the best estimates, at this point in time, of the influence of these attributes. It does not provide a once and for all answer. It is expected that as research continues, modification will become necessary"
- The rail market in Great Britain has changed significantly in recent years. Time based elasticities could well have fallen as a result of the digital revolution and the ability to use train travel time in a very useful manner. Frequency penalties and elasticities might have been impacted by the now widespread use of advance purchase tickets which offer price discounts, sometimes very large, but at the expense of having to commit to a specific train departure. Interchange penalties and elasticitites might also have fallen because of the considerably greater amount of on-line information on live train running, station layouts and facilities, and onward frequencies
- There was a view within the rail industry, perhaps influenced by the experiences of high speed trains, that the larger time savings achievable on conventional train services might attract a higher elasticity. There was also a feeling, perhaps influenced by the loss aversion literature and its adoption within mainstream Stated Preference work, that deteriorations in rail service quality might have a larger demand impact than equivalent improvements.
- There have been piecemeal updates over the years in GJT elasticities, frequency penalties and interchange penalties and these have not necessarily maintained the required consistency between each. This study builds upon the Wardman and Whelan (2004) study in directly estimating a consistent set of frequency penalty, interchange penalty and GJT elasticity.
- There remains relatively little reported research into how timetable related service quality impacts on rail demand, particularly distinguishing between short and run effects.

The research reported here contributes to each of these area where further research is warranted.

3. DATA

For this study we made use of two datasets. Firstly, we utilised data collected specifically for this study. This covered 356 flows between Non London stations. Four-weekly data was obtained for the years 2005 to 2010. The flows within this dataset include those which have had large changes in GJT over the period in question. Secondly, we used data from a previous study (Wardman and Whelan, 2004). The latter data was specifically selected to examine changes in GJT and its constituent parts. It is four-weekly, covering 1995 to 2000 and 756 Non London flows. The only service quality variables included in these datasets were the timetable related ones of in-vehicle time, service frequency, the number of changes of train needed and any interchange connection time. It was beyond the scope of the study to assemble historic data on other aspects of rail service quality and indeed on competition from other modes.

The reasons for focussing upon inter-urban flows that exclude journeys to and from London are that the latter are different in nature covering higher quality services where business travel is much more prevalent and there tends to be little variation in GJT on London flows. In any event, flows to and from London are very small in number compared to flows to and from everywhere but London.

Models without lags (static models) contain 73913 observations from 950 flows. This falls to 67360 observations when models with lagged structures are specified. Importantly, the data splits GJT into its component parts and in addition, and originally, distinguishes connection time, where interchange occurs, from station-to-station time. This is crucial for examining the weights and functional form of GJT. In terms of explanatory variables we have GJT for flow i in time t (GJT_{it}), average revenue yield per flow (revenue divided by number of trips – $Fare_{it}$), gross value added for the origin (GVA_{it}) and flow distance (D_i). Other external factors such as car ownership, fuel prices, car journey times and bus fares and times tend to be highly correlated with GVA or else route-specific historical data is difficult to obtain or unreliable. Nonetheless, these variables are expected to have a much lesser effect on rail demand than the key GVA term[3]. In any case we include cross sectional fixed effects in our modelling which should control for any systematic (time invariant) influence of these covariates.

4. METHOD

4.1 Estimation Framework: Error Correction Model

Given that we have four weekly data, it is reasonable to assume that there is some delay in adjustment of rail demand to changes in the explanatory factors. As such there is a need to model explicitly the evolution of the response of demand; the model is dynamic. We estimate an Error Correction Model (ECM). ECMs are widely used in dynamic econometric modelling and have been applied in railway demand modelling (Kulshreshta et al (2001), NERA (2003),

[3] Our experience from modelling the effect of a wide range of external factors on rail demand is that the estimated elasticities to GJT and fare are insensitive to the set of external factors included in the model. Of course, the elasticities to external factors are very sensitive to the set of external factors included.

Meaney et al (2005)) and wider transportation planning over a number of years (Samimi (1995), Ramanathan, R. (2001), Li et al (2006), Marazzo et al (2010)). Many econometrics textbooks included treatment of ECMs, see for example Greene (2012).

An ECM distinguishes between an equilibrium long run relationship and a short run adjustment path towards the equilibrium. Unlike the more simplistic partial adjustment model (PAM) the ECM does not impose a common long-run multiplier (one period effect/long run effect) across explanatory variables; that is, the long run multiplier can be different for a GJT change than for a fare change. Further, the ECM is not constrained to a geometric adjustment path as various short run lags can be included for each explanatory variable. The ECM is also robust to spurious regression, but still allows the quantification of cointegrating (long run) relationships.

An important point to note is that the dependent variable in an ECM is not the level of demand but the difference of two consecutive periods of demand, and an important implication of this is that the multiple correlation coefficient (R^2) for the ECM is not comparable to a regression in levels (the static regression shown for comparison in the results).

A generic representation of the ECM, which is the model underpinning all the results reported here except for a static model reported for comparative purposes, is:

$$\begin{aligned}\Delta\ln(\mathrm{V}_t) &= \alpha + \varphi(\ln(\mathrm{V}_{t-1}) - \beta_1\ln(\mathrm{GJT}_{t-1}) - \beta_2\ln(\mathrm{Fare}_{t-1}) - \beta_3\ln(\mathrm{GVA}_{t-1})) \\ &+ \tau_1\Delta\ln(\mathrm{GJT}_t) + \tau_2\Delta\ln(\mathrm{Fare}_t) + \tau_3\Delta\ln(\mathrm{GVA}_t) + \ldots\end{aligned} \tag{6}$$

where Δ is the difference operator ($\Delta X_t = X_t - X_{t-1}$). The intuition behind the model is that there is a set of short run dynamics $\Delta\ln(V_t)$ on the left hand side and the other Δ augmented variables on the right hand side. The "..." in the specification above indicates that there can be further lagged values of the explanatory variables in Δ transform which would imply a more flexible dynamic path of adjustment.

However, there is also a long run relationship given within the bracket parameterised by φ. In equilibrium the term within the bracket equals zero. If there is a shock to the model, demand temporarily does not equal the long run relation and the model is in disequilibrium. Provided φ is negative, over subsequent periods the model tends back to equilibrium at a rate given by φ. As such the short run GJT elasticity is given by τ_1 and the long run elasticity is β_1. In practice the long run relationship is calculated by taking the negative ratio of the coefficient on $\ln(GJT_{t-1})$ and $\ln(V_{t-1})$, given in practice we estimate $-\varphi\beta_1$ on $\ln(GJT_{t-1})$ in a regression.

4.2 Panel data formulation and estimation

We have panel data available for this study and so equation (6) is augmented with cross sectional as well as time subscripts:

$$\begin{aligned}\Delta\ln(\mathrm{V}_{it}) &= \alpha_i + \varphi(\ln(\mathrm{V}_{i,t-1}) - \beta_1\ln(\mathrm{GJT}_{i,t-1}) - \beta_2\ln(\mathrm{Fare}_{i,t-1}) - \beta_3\ln(\mathrm{GVA}_{i,t-1})) \\ &+ \tau_1\Delta\ln(\mathrm{GJT}_{i,t}) + \tau_2\Delta\ln(\mathrm{Fare}_{i,t}) + \tau_3\Delta\ln(\mathrm{GVA}_{i,t}) + \ldots\end{aligned} \tag{7}$$

$i = 1,...,N$

We estimate models using flow specific fixed effects (α_i). These control for unobserved factors that are flow invariant and are important to guarantee unbiased estimates of the coefficients of interest. However it is well known that in the presence of fixed effects, the dummy variable estimator (fixed effects estimator) is not a consistent estimator as the number of flows gets large. This motivates the use of dedicated dynamic panel instrumental variable (IV) estimators (e.g. Arellano and Bond (1991) and Blundell and Bond (1998)).

Note, however, that we are using 4 weekly data. This actually gives a very long time series (many flows have 5x13=65 periods). As such we can invoke large sample properties in T and thus fixed effects estimation produces unbiased parameter estimates. To verify this result we did implement Arellano and Bond (1991) estimation for models initially developed within this study (models that resemble the ECM reported under Model IX in the results section). The results were extremely similar. Our conclusion on most appropriate estimator would be different if we were using annual rather than four weekly data (for example contrast to the 2009 rail demand study in Britain by Oxera (2010)).

In all our specifications we have additionally included 12 further dummy variable fixed effects which capture the influence of common factors in each of the 13 time periods per annum (the first period dummy removed to avoid perfect collinearity with the constant). This is equivalent to the season effects included when using seasonal (3 monthly) data.

We estimate the models using Eviews 6 (Quantitative Micro Software, 2007). We use the fixed effects least squares estimation routine, which can incorporate both linear and non-linear parameterisations. Non-linear parameterisations are required for GJT components (see 4.3.2) and generalised cost approaches (see 4.3.4). The Eviews 6 software also provides the necessary dynamic panel techniques to verify that adopting the simpler fixed effects approach does not bias parameter estimates relative to Arellano and Bond (1991), as expect and discussed above.

4.3 Variations on the base specification

Equation (7) represents the base specification. We now describe several variations on this specification.

4.3.1 Variation of the GJT Elasticity

A key element of the research was to examine whether the elasticity of demand with respect to GJT is different depending on the size and magnitude of the change. We modelled this by including relevant interaction variables with ln(GJT). In particular, we reformulate the long run relation in (7) which is the part of (7) which is within the bracket parameterised by φ. We restricted the interactions to be in the long run relationship as we could not find statistically significant interactions with short run components. Thus whilst we find some evidence for variation of the long run relationship with these characteristics, but not for the short run dynamics.

The revised formulation of the long run relationship is:

$$\begin{pmatrix} \ln(V_{i,t-1}) - \beta_1 \ln(GJT_{,it-1}) - \beta_2 \ln(Fare_{i,t-1}) - \beta_3 \ln(GVA_{i,t-1}) \\ -\lambda_1 \ln(GJT_{i,t-1})SIZE_{i,t-1} - \lambda_2 \ln(GJT_{i,t-1})POS_{i,t-1} \end{pmatrix} \tag{8}$$

where SIZE is the percentage change in GJT for the flow over the past 13 periods (1 year), POS is a dummy variable taking the value one if GJT increased over the past 13 periods. This implies that the elasticity of demand with respect to GJT is $\beta_1 + \lambda_1 SIZE_{i,t-1} + \lambda_2 POS_{i,t-1}$.

We can further add in interactions with distance and value for money (fare or generalised cost per unit distance) to allow the GJT elasticity to vary by these flow characteristics.

4.3.2 Model with estimated weights on the components of GJT

In (7) and in (8) GJT is input into the model as that computed from the raw data using the specification for GJT in PDFH (ATOC, 2013). However in this variation of the model, we wish to understand whether the weights on each component are supported by this dataset. Thus we replace GJT in (7) with an aggregator function of the components of GJT. Importantly in this variation (contrast to 4.3.4) we maintain the GJT aggregator concept but examine whether this data supports the weighting of the components in the function as specified in PDFH.

(7) becomes:

$$\begin{gathered} \Delta \ln(V_{it}) = \alpha_i + \varphi \begin{pmatrix} \ln(V_{i,t-1}) - \beta_1 \ln(IVT_{i,t-1} + \gamma_1 H_{i,t-1} + \gamma_2 I_{i,t-1} + \gamma_3 C_{i,t-1}) \\ -\beta_2 \ln(Fare_{i,t-1}) - \beta_3 \ln(GVA_{i,t-1}) \end{pmatrix} \\ + \tau_1 \Delta \ln(IVT_{i,t-1} + \gamma_1 H_{i,t-1} + \gamma_2 I_{i,t-1} + \gamma_3 C_{i,t-1}) + \tau_2 \Delta \ln(Fare_{i,t}) + \tau_3 \Delta \ln(GVA_{i,t}) + \ldots \end{gathered} \tag{9}$$

Where IVT is train time (in vehicle time), H is headway, I is the number of interchanges and C is the connection time. Note that (9) is non-linear in parameters, whilst (7) is linear in parameters. The estimation routine in Eviews allows for non-linear estimation.

4.3.3 Model without GJT: Separate elasticities on service characteristics

We then consider relaxing the GJT concept and estimate models with separate components (SC model). (7) is reformulated by replacing the GJT with three terms:

$$\begin{gathered} \Delta \ln(V_{it}) = \alpha_i + \varphi \begin{pmatrix} \ln(V_{i,t-1}) - \beta_1 \ln(IVT_{i,t-1}) - \beta_2 \ln(H_{i,t-1}) - \beta_3 I_{i,t-1} \\ -\beta_4 C_{i,t-1} - \beta_5 \ln(Fare_{i,t-1}) - \beta_6 \ln(GVA_{i,t-1}) \end{pmatrix} \\ + \tau_1 \Delta \ln(TT_{i,t}) + \tau_2 \Delta \ln(H_{i,t-1}) + \tau_3 \Delta I_{i,t-1} + \tau_4 \Delta C_{i,t-1} + \tau_5 \Delta \ln(Fare_{i,t}) + \tau_6 \Delta \ln(GVA_{i,t}) + \ldots \\ i = 1, \ldots, N \end{gathered} \tag{10}$$

I and C are entered in this form (not logged) since they can be zero. Their coefficients therefore represent the proportionate effect on demand of an additional interchange or a unit change in connection time. It is important to emphasise that this specification is different to that in equation (9). In (9) the GJT concept is maintained and as such the elasticities of the separate components on demand are given by the relationship in equations (2,3,4). In equation (10), each component has its own long run and short run elasticity, not bound by the relationships implicit in GJT.

4.3.4 Model with Generalised Cost: Combining Generalised Journey Time and Fare into a single index

In this variation we are interested in whether a more simplified formulation of combining GJT and fare into a single index fits the data well and thus is a useful simplification. Generalised Cost (GC) is specified as:

$$GC = P + \varpi GJT \tag{12}$$

where τ is the money value of time. We are in the fortunate position of being able to freely estimate ϖ with the demand model using non-linear least squares estimation, thereby getting the value of time that best fits the data, as well as the more conventional position of using the most appropriate ϖ suggested by previous studies.

(7) becomes:

$$\begin{aligned}\Delta \ln(V_{it}) &= \alpha_i + \varphi\left(\ln(V_{i,t-1}) - \beta_1 \ln(GC_{i,t-1}) - \beta_2 \ln(GVA_{i,t-1})\right) \\ &+ \tau_1 \Delta \ln(GC_{i,t}) + \tau_2 \Delta \ln(GVA_{i,t}) + \ldots \\ i &= 1,\ldots,N\end{aligned} \tag{13}$$

5. RESULTS

In this section we outline our findings with respect to the three strands of analysis conducted on Non London flows and for tickets other than seasons. Firstly, we examine in section 5.1 if the response to changes in GJT differs depending on the size and sign of the GJT change and if the response is a function of trip distance and value for money of travel (in terms of fare). Secondly, we consider in section 5.2 whether the current formulation of GJT specifies the appropriate weights by estimating a model with freely varying weights. Thirdly, we consider in section 5.3 whether it is better to dispense with the GJT concept and either replace it with separate components (no index function) or alternatively add GJT to fare via some exogenous or endogenous weight to form a Generalised Cost model.

Given that in this application there are numerous fixed effects in both the cross sectional and period dimensions and that their individual magnitudes are not of direct interest, we do not report them.

5.1 Variation of GJT Elasticity

As described in 4.3.1 of the methodology section, we have examined how the GJT elasticity varies with:

- Introducing dynamic (lag) adjustment effects (Model II onwards)
- The size of the GJT change (Model III)
- The sign of the GJT change (Model III)
- Distance (Model III)
- Value for Money - Price per Mile (PpM) (Model IV)
- Value for Money - Generalised Cost per Mile (GCpM) (Model V)

The results based around the existing GJT formulation are reported in Table 1. Model I is the standard model without any dynamics. The fare elasticity is higher than the PDFH recommended figure ranging between -0.85 and -1.00 for Non-London non-season flows and the GJT elasticity is clearly somewhat larger than the then recommended figure of between -0.7 and -1.1 (which depended upon whether the GJT variation resulted from time and frequency variations or interchange variations). Nonetheless, the elasticities are not unreasonable and are very precisely estimated. At face value, the results suggest that there might be support for larger GJT variations having larger elasticities given our data set contains more larger changes than is customary.

Table 1: GJT Models – Elasticity Variation and Current GJT Formulation

	I	II	III	IV	V
Reference Equation in Section 4		(7)	(8)	(8)	(8)
Fare	-1.274 (125.0)				
GJT	-1.461 (85.9)				
GVA(1)	-1.926 (19.9)				
GVA(2)	1.118 (29.7)				
VOL_{t-1}		-0.454 (139.5)	-0.486 (135.0)	-0.453 (139.3)	-0.454 (139.5)
$Fare_{t-1}$		-0.716 (56.2)	-0.752 (52.6)	-0.582 (23.9)	-0.717 (56.1)
GJT_{t-1}		-0.640 (42.1)	-0.800 (33.6)	-0.613 (38.9)	-0.638 (29.9)
ΔFare		-0.866 (82.9)	-0.868 (78.1)	-0.863 (82.6)	-0.866 (82.9)
ΔGJT		-0.395 (9.5)	-0.388 (9.3)	-0.393 (9.5)	-0.395 (9.5)
$\Delta Fare_{t-1}$		0.098 (7.8)	0.107 (7.9)	0.091 (7.3)	0.098 (7.8)
$\Delta Fare_{t-2}$		0.061 (5.8)	0.065 (5.8)	0.056 (5.4)	0.061 (5.8)
GJT_{t-1}*Miles			0.00082(3.8)		
GJT_{t-1}Size			-0.035 (8.9)		
GJT_{t-1}Sign			0.011 (10.1)		
GJT_{t-1}*PpM				-0.143 (6.5)	
GJT_{t-1}*GCpM					-5.4E-07 (0.1)
$GVA(1)_{t-1}$		-0.773 (9.6)	-0.657 (7.5)	-0.765 (9.5)	-0.772 (9.6)
$GVA(2)_{t-1}$		0.514 (15.6)	0.381 (9.4)	0.511 (15.6)	0.514 (15.5)
Adj R^2	0.957	0.329	0.344	0.329	0.329

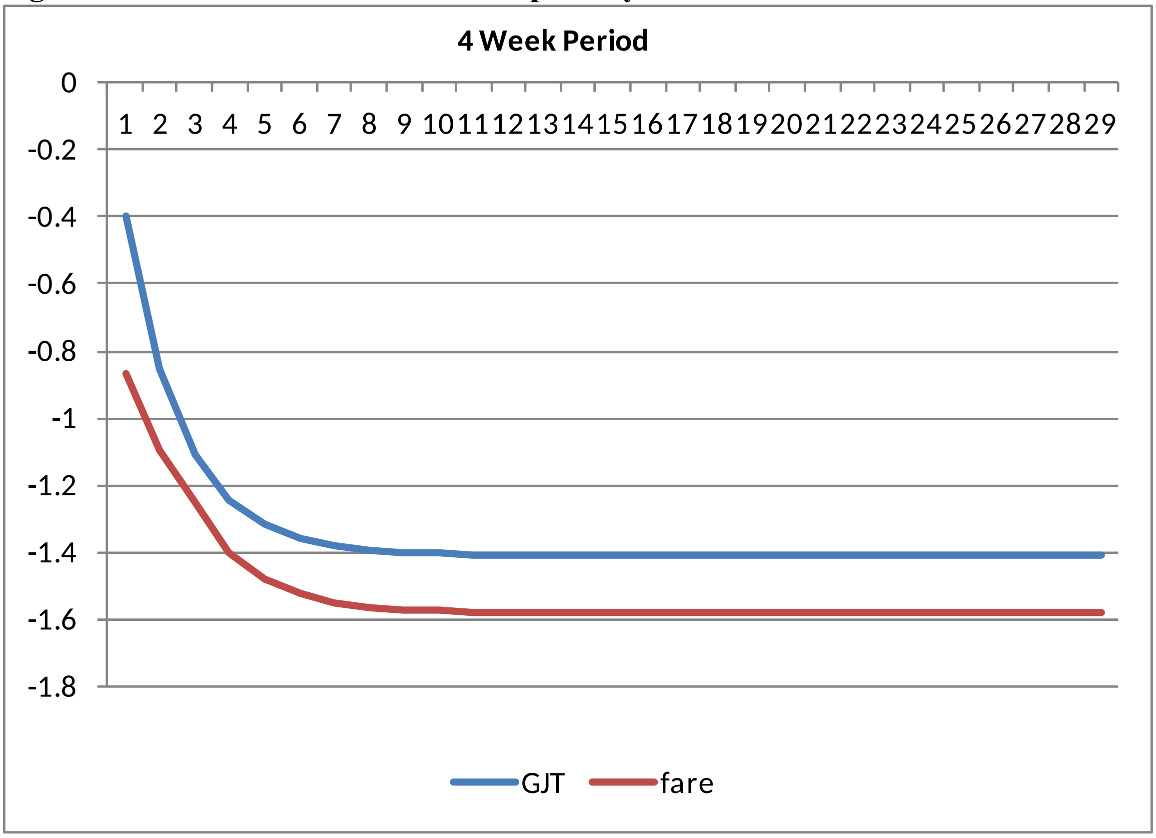
|t stats| in (.)

Two GVA elasticities are specified; one for the bespoke data (GVA(1)) and one for the GJT reformulation study data (GVA(2)). The reason for this that the recent period has witnessed continued increases in rail demand associated with a lower GDP and hence GVA(1) is negative. This trend has been recognised in the railway industry and a negative GDP elasticity has been recovered in other recent analyses of rail ticket sales. Although GVA(2) is at the upper end of the 0.85 to 1.1 range depending upon distance recommended by PDFH, it must be borne in mind that it will also have discerned upward trends in rail demand due to fuel price increases and increased levels of road congestion.

Overall, the data would appear to provide a firm basis for examining the GJT elasticity and variations in its specification.

Model II specifies a dynamic model in the form of an Error Correction Model (ECM). Recall that the R^2 is not comparable with the static model due to a different dependent variable in the ECM. When estimating the model we have to choose the number of lagged differenced terms (Δ variables in Table 1) for the explanatory variables. These form the short run dynamics. We have chosen the terms based on a general to specific methodology coupled with inspection of the graph of the elasticities as they evolve over time following a change in each explanatory variable. In particular we did not include terms if there was an implausible transition such as over shooting (which often then had under shooting). Figure 1 shows the plot of the GJT and Fare elasticities for Model II.

Figure 1: GJT and Fare Elasticities Implied by Model II



The SR and LR GJT elasticities in Model II are -0.39 and -1.41. The corresponding figures for the fare elasticity are -0.87 and -1.58. For GVA the LR elasticities are -1.70 and 1.13 i.e. not too dissimilar to the static model. It can be seen that the LR elasticity is reached (at least 95% of the transition) within 0.5 years (7 periods).

Model III introduces a size and sign effect on GJT and also allows the GJT elasticity to vary with distance. Section 4 described how we tested for size and sign effects. Both the size ($GJT_{t-1}Size$) and sign ($GJT_{t-1}Sign$) coefficients are highly statistically significant. However, as is apparent from Table 2 which provides LR GJT elasticities for a wide range of proportionate increases and reductions in GJT, the impact of these effects is trivial!

The distance effect in Model III (GJT_{t-1}Miles) is also significant and indicates that the LR GJT elasticity will fall with distance, as can also be seen in Table 10. We might expect the GJT elasticity to increase with distance on the grounds that mandatory commuting trips with relatively low elasticities will tend to be more common for shorter journeys whilst time sensitive business trips will tend to form a larger proportion of longer distance trips. The activities associated with longer distance trips might be expected to be more important given the greater amount of time required to pursue them. In addition, one of the strongest relationships apparent for the value of time is that it increases with distance (Abrantes and Wardman, 2011) and this might operate to excerpt an upward effect on the GJT elasticity also. Offsetting this is that rail elasticities can also be expected to vary with market share, being higher where rail's position is weaker, and rail faces more competition in shorter than longer distance markets.

On balance, we expect that there is theoretical support for the GJT elasticity increasing with distance, and indeed this was supported by the meta-analysis. Whilst our results are at odds with this, it should be pointed out that the median trip length was 81 miles and that most Non-London inter-urban trips are less than 150 miles, whereupon the amount of implied GJT elasticity variation is relatively minor.

Table 2: Long Run GJT Elasticity by Size, Sign and Distance

	Proportion Change in Year on Year GJT										
Miles	0.5	0.4	0.3	0.2	0.1	0	-0.1	-0.2	-0.3	-0.4	-0.5
20	-1.625	-1.618	-1.611	-1.604	-1.597	-1.613	-1.620	-1.628	-1.635	-1.642	-1.649
50	-1.575	-1.568	-1.561	-1.554	-1.546	-1.563	-1.570	-1.577	-1.584	-1.591	-1.599
80	-1.524	-1.517	-1.510	-1.503	-1.496	-1.512	-1.520	-1.527	-1.534	-1.541	-1.548
100	-1.491	-1.484	-1.477	-1.469	-1.462	-1.479	-1.486	-1.493	-1.500	-1.507	-1.514
150	-1.407	-1.400	-1.392	-1.385	-1.378	-1.395	-1.402	-1.409	-1.416	-1.423	-1.430
200	-1.323	-1.316	-1.308	-1.301	-1.294	-1.311	-1.318	-1.325	-1.332	-1.339	-1.346
250	-1.239	-1.231	-1.224	-1.217	-1.210	-1.226	-1.234	-1.241	-1.248	-1.255	-1.262
300	-1.154	-1.147	-1.140	-1.133	-1.126	-1.142	-1.150	-1.157	-1.164	-1.171	-1.178
350	-1.070	-1.063	-1.056	-1.049	-1.042	-1.058	-1.065	-1.073	-1.080	-1.087	-1.094

Model IV tests a value for money interaction specified as the price per mile. We might expect that rail tends to become less attractive as the price per mile increases and hence the GJT elasticity would tend to increase as rail's market share tends to fall. As against that, it could be argued that rail service quality improvements will be less attractive where rail is regarded to provide lower value for money as price per mile increases.

It might then be that as a result of these two conflicting expectations, the variation in the GJT elasticity with respect to pence per mile is not very great, even though the interaction coefficient estimate (GJT_{t-1}*PpM) is highly significant. For VFM=0.1 the long run GJT elasticity estimate is -1.382 while for 0.6 it is -1.540; thus a small increase in the absolute value with VFM.

The value per money measure based on price per mile is not a complete representation of the overall attractiveness of rail since GJT itself will have a bearing. We therefore entered generalised cost (GC) per mile as the measure of attractiveness. It was specified as the mean across time periods for each flow. Its interaction (GJT_{t-1}*GCpM) turned out to be far from significant and to imply essentially a constant GJT elasticity with regard to GC per mile.

5.2 GJT Weights

Here we examine the impact of varying weights used to construct GJT. Given our findings of either very small variation or counter intuitive variation with the characteristics considered above, we do not report specifications with these interactions alongside this further analysis. Our conclusions do not differ from those above if we do include such interactions. An original aspect of this work is to enhance the GJT approach by isolating connection time at the interchange station and on-train time. The three basic model forms we have estimated are:

- Freely estimate the weights to connection time, headway and the interchange penalty (as described in 4.3.2);
- Impose weights based on ‘best evidence’;
- Estimate scales to the existing PDFH weights.

The models (VI to IX) are reported in Table 4 below. Before discussing the results, we describe the key features of each model.

Model VI simply takes the amounts of interchange connection time, headway and the number of interchanges and estimates parameters to these without the modifiers (eg, by distance, ticket type and frequency) applied in PDFH. Time has a coefficient of one within GJT.

Models VIII and IX are based around the estimation of scales to the existing PDFH recommended weights for interchange, headway and connection time. They therefore retain the particular relationships apparent with respect to distance and frequency but test whether a scale transformation of the absolute weights can better explain variations in travel demand.

Model VII imposes weights on the need to interchange and on the headway and connection time based on what we regard to be ‘best evidence’. It is some time since the PDFH frequency and interchange penalties were derived in their particular form, and they have undergone amendment, whilst connection time has defaulted to the same value as in-vehicle time. We now set out the multipliers we have used to convert headway, interchange and connection time into units alongside on-train time within a revised specification of GJT.

The interchange penalty valuation function, which provides a variable penalty across different situations, was estimated in a study of interchange for the Strategic Rail Authority (Wardman and Shires, 2001) and was based on analysis of RP and SP data: This estimated the time valuation of interchange (VoI) as:

$$VoI = [7.16 - 1.25SE + (0.066 - 0.013SE)T]I^{0.7} \tag{12}$$

where *SE* denotes the South East, *T* is the train journey time and I denotes the number of interchanges. The model was estimated to either one or two interchanges and the purpose of the power term (0.7) was to determine that two interchanges are valued only 62% more than one interchange. Where interchange is less than one, the power term is ignored. PDFH provides values by distance but they are not pure interchange penalties and we return to a comparison below.

The headway and connection wait time multipliers used are taken from the recent large scale meta-analysis of values of time reported by Abrantes and Wardman (2011). The headway value in time units (VoH) is:

$$VoH = e^{-0.448} D^{-0.042IU} \tag{13}$$

D is distance in miles and IU is an inter-urban journey over 20 miles. For urban journeys VoH is 0.64. It falls to 0.54, 0.53 and 0.51 at 50, 100 and 200 miles respectively. These contrast somewhat with PDFH figures which range from 1.00 at 5 minute headways through to 0.53 and 0.33 at two hourly headways for full/season and reduced tickets respectively.

The value of waiting time at the interchange (VoW) in time units is

$$VoW = e^{0.317} W^{0.075} D^{-0.042IU} \tag{14}$$

where additionally W is the amount of waiting time. VoW tends to be less than the conventional multiplier of 2, although PDFH does not place any premium weight on connection time. Note that these are standard wait time values. They do not, for example, reflect low connection times having relatively high values because of the greater risk of missing a connection or that some time at an interchange station can be used for benefit.

Table 3 provides a comparison of the overall time based deterrence of an interchange with various amounts of connection time based on what we here term best evidence and the PDFH values. What we observe, as we would expect since PDFH does not apply a premium to wait time, is that for shorter connection times PDFH tends to provide larger values and for longer connection times it tends to provide smaller values. PDFH values also exhibit somewhat larger distance effects.

Table 3: Overall Interchange Valuations using PDFH and Best Evidence Weights

Miles	Minutes	Wait	PDFH	Best evidence
10	20	15	28	34
		30	43	62
		45	58	91
		60	73	120
50	60	15	40	33
		30	55	56
		45	70	81
		60	85	106
100	100	15	55	35
		30	70	58
		45	85	82
		60	100	106
200	180	15	80	39
		30	95	62
		45	110	85
		60	125	109

Model VI in Table 4 which freely estimates the weights actually provides the best fitting model of the four reported whilst Model VII based upon what we have termed the best empirical evidence relating to the weights for headway (Weight_H), interchange (Weight_I) and connection time (Weight_C) achieves the poorest fit of the four!

In Model VI, Weight_H is around 40% of train time. For inter-urban and urban Non London flows, PDFH recommendations for the service interval penalty range from 1.0 at every 10 minutes to figures in the range 0.5 to 0.6 at hourly intervals. Thus the freely estimated values are somewhat lower than PDFH recommendations. Interchange is estimated to have a value of around 100 minutes. The average distance in our data set is around 100 miles, implying a PDFH interchange penalty of 40 minutes. With average wait times less than an hour, this implies that our results are placing more weight on interchange than is currently the case. Connection time is valued at 83% of train time. However, it is not significantly different from having a value of one.

The SR and LR GJT elasticities in Model VI are -0.27 and -0.81. The latter is in line with then current PDFH recommendations (ATOC, 2009). The corresponding figures in Model VII based on the weights which are taken as best evidence are a little larger at -0.36 and -0.94 respectively.

Models VIII and IX retain the PDFH relationships between interchange and distance and between the service interval penalty and the service interval but allow their absolute magnitude to differ. In Model VIII we find that connection time is again valued less highly than train time, and this time the difference is statistically significant.

However, we do not find it credible that connection time is valued less highly than on-train time and hence have constrained connection time to have the same weight as train time. This is reported as Model IX. It finds strong support for the current PDFH frequency penalties but, as is implied by Model VI, it indicates that somewhat more weight should be placed on interchange.

The SR and LR GJT elasticities for Model IX are -0.31 and -1.08, the latter corresponding with the PDFH recommended GJT elasticity where interchange is the source of the GJT variation.

Table 4: Varying the GJT Weights

	VI	VII	VIII	IX
Reference equation in Section 4	(9)	(7) (but revised GJT)	(9) (but revised component calculations)	(9) (but using components pre-weighted by PDFH factors)
VOL_{t-1}	-0.459 (140.2)	-0.436 (135.4)	-0.456 (139.9)	-0.456 (139.9)
$Fare_{t-1}$	-0.723 (56.8)	-0.752 (58.7)	-0.719 (56.2)	-0.720 (56.3)
GJT_{t-1}	-0.370 (20.5)	-0.411 (29.4)	-0.535 (22.2)	-0.494 (24.3)
ΔFare	-0.872 (84.7)	-0.891 (85.9)	-0.866 (83.2)	-0.867 (83.2)
ΔGJT	-0.266 (9.6)	-0.357 (8.9)	-0.339 (9.1)	-0.308 (9.1)
Weight_H	0.444 (9.0)	Equation 13	0.871 (10.15)	1.001 (10.67)
Weight_I	97.996 (10.1)	Equation 12	1.653 (14.8)	1.766 (14.3)
Weight_C	0.832 (5.3)	Equation 14	0.638 (7.5)	1.0 (Fixed)
$\Delta Fare_{t-1}$	0.090 (7.2)	0.106 (8.4)	0.097 (7.8)	0.098 (7.8)
$\Delta Fare_{t-2}$	0.057 (5.4)	0.066 (6.3)	0.061 (5.8)	0.061 (5.8)
$GVA(1)_{t-1}$	-0.854 (10.5)	-0.654 (7.9)	-0.889 (10.9)	-0.897 (11.0)
$GVA(2)_{t-1}$	0.644 (20.0)	0.830 (26.4)	0.537 (16.2)	0.524 (15.9)
Adj R^2	0.331	0.320	0.330	0.330

|t stat| is (.)

We also examined whether the connection time weight varied with the amount of connection time, on the grounds that very short connection times are disliked because they are risky and long ones are disliked because wait time has a premium value and there is a limit to how much wait time can be used ‘productively’. There was some variation in the connection time weight across different bands, with a higher value for 0-10 minutes than for 10-20 minutes, and indeed the latter was insignificantly different from zero, and then a higher weight for connection time in excess of 20 minutes. However, we do not find it credible that the connection time value for 10-20 minutes is actually zero whilst it is anyway a very narrow range of connection time and, moreover, the weights for the other two categories did not exceed one. We therefore did not retain this segmentation.

5.3 Variants upon GJT and Fare Model

We here report models based on GC and which estimate separate demand parameters for train time, headway, interchange and connection time.

In constructing GC, we use the value of time (VoT) recommended in PDFH. Converted to 2005 prices and incomes, this is:

$$VoT = 1.14GVA^{0.723}D^{0.184}e^{-4.378+0.258IU+0.968EB} \tag{15}$$

GVA is in per capita units (2005 is 3944), D is distance in miles, IU denotes an inter-urban journey of over 20 miles and EB is employer’s business. Values of time are calculated for business travel and leisure travel for each year, according to its income level, and for the distance on the flow.

The GC model based upon this formula is reported as Model X (GC(1)) in Table 5. An alternative approach is to freely estimate the value of time. We have done that here, forcing the value of time to grow in line with income which is common practice, and this is reported as Model XI (GC(2)) in Table 5. Comparing the current PDFH model albeit with more weight placed upon interchange, which is Model IX, we can see that it produces a better fit than both the GC models. Indeed, Model II of Table 2 which is based on current PDFH recommendations also provides a better fit than the GC models.

Comparing the two GC models, GC(1) has a mean value of time of 14.9 pence per minute, a LR GC elasticity of -2.58 which implies LR GJT and fare elasticities of -1.68 and -0.89 respectively. In contrast, GC(2) provides a mean value of time of only 2.8 pence per minute, far less than we would ever attribute to it based on official values or previous evidence. Given the LR GC elasticity of -2.28, the implied LR GJT and fare elasticities are -0.64 and -1.63. These are more in line with the balance between the GJT and fare elasticities obtained from Model IX of -1.08 and -1.58 but neither of the GC models imply GJT and fare elasticities that correspond closely with the directly estimated values of Model II and Model IX.

Turning to the separate component models (Models XII and XIII), these actually provide better fits to the data than the GJT specification. However, Model XII returns a wrong sign effect for connection time. We therefore merged it with in-vehicle time (IVT) and the resulting model is reported as SC(2).

It recovers significant coefficients for headway (Head), the number of interchanges (Int) and the combined IVT and connection time term (IVTConn). The SR elasticities for IVTConn and headway are -0.11 and -0.10, with LR elasticities of -0.48 and -0.21. In the SR, an additional interchange would reduce demand by 13%, increasing to 37% in the long run.

The meta-analysis conducted in Wardman (2012) found the journey time elasticity to increase with distance. The LR value varied between -0.57 at 2 miles to -1.41 at 200 miles. The elasticity estimated here would indicate that these are too high, in line with the findings that the GJT model would place less emphasis on time relative to interchange. For headway, the meta-analysis recovered LR elasticities of -0.50 for urban and -0.27 for inter-urban trips. Given the majority of our flows are inter-urban our LR headway elasticities are broadly consistent with previous evidence.

5.4 Preferred Model and Implied Elasticity Variation

Given the retention of the GJT approach, which is any event statistically superior to the GC approach, our preference is for Model IX. We have not found any convincing support for variation in the GJT elasticity. Model IX performs better than all but one of the other GJT models tested. Model VI is statistically preferable but would involve larger changes to industry practice to accommodate the changes. In any event, Model IX and Model VI are similar in attaching greater importance than currently to interchange and retaining the connection time weight of one.

Table 5: Different Model Formulations – GC, GJT and Fare, and Separate Components

	X	XI	IX	XII	XIII
Reference equation in Section 4	(13) (fixed VoT)	(13) (model estimated VoT)	(9) (but using components pre-weighted by PDFH factors)	(10)	(10) (combined IVT and Connection time)
	GC(1)	GC(2)	GJT	SC(1)	SC(2)
VOL_{t-1}	-0.419 (136)	-0.431 (138)	-0.456 (139)	-0.458 (140)	-0.461 (141)
$Fare_{t-1}$			-0.720 (56.3)	-0.728 (57.1)	-0.724 (56.9)
GJT_{t-1}			-0.494 (24.3)		
GC_{t-1}	-1.080 (66.6)	-0.980 (67.7)			
IVT_{t-1}				-0.183 (9.6)	
$IVTConn_{t-1}$					-0.219 (14.5)
$Head_{t-1}$				-0.093 (15.0)	-0.098 (15.9)
Int_{t-1}				-0.241 (37.0)	-0.212 (35.3)
$Conn_{t-1}$				0.00016 (0.4)	
ΔFare			*-0.867 (83.2)*	*-0.878 (84.7)*	*-0.876 (84.7)*
ΔGJT			-0.308 (9.1)		
ΔGC	-1.889 (84.5)	-1.248 (78.0)			
ΔIVT				-0.139 (2.3)	
ΔHead				-0.090 (5.1)	-0.098 (5.5)
ΔInt				-0.184 (9.3)	-0.134 (7.4)
ΔConn				0.0019 (3.4)	
ΔIVTconn					-0.111 (2.4)
Weight_H			1.001 (10.67)		
Weight_I			1.766 (14.3)		
Weight_C			1.0 (Fixed)		
VOT		0.957 (23.0)			
$\Delta Fare_{t-1}$			0.098 (7.8)	0.092 (7.4)	0.089 (7.1)
$\Delta Fare_{t-2}$			0.061 (5.8)	0.058 (5.5)	0.056 (5.3)
$GVA(1)_{t-1}$	1.067 (12.4)	0.167 (1.8)	-0.897 (11.0)	-0.958 (11.5)	-0.921 (11.1)
$GVA(2)_{t-1}$	0.864 (31.6)	1.229 (44.7)	0.524 (15.9)	0.559 (16.4)	0.468 (14.2)
Adj R^2	0.311	0.315	0.330	0.331	0.332

|t stat| is (.)

6. CONCLUSIONS

In this paper we have tested using a dynamic econometric model the suitability of the framework long adopted in Great Britain of using GJT in rail demand forecasting and the parameters and elasticities that populate that framework. This has been based on a very large data set of rail ticket sales. There are a number of original aspects to the research and its findings, providing insights of a methodological nature as well as contributing fresh empirical evidence in an area where there is little published evidence. We should also point out that this is an issue of some significance; faster journey times, improved frequencies and, in particular, the removal of the need to interchange can provide substantial increases in rail demand.

Firstly, we have investigated whether there needs to be a departure from a constant GJT elasticity through examining variations with size and sign of the GJT change and variation with trip distance and value for money. We find little evidence to depart from such a constant elasticity form.

Secondly, we have considered whether the weights on the components of GJT are appropriate, in the light of piecemeal amendments to official recommendations over the years. The evidence indicates that more weight should be placed on interchange within the

GJT formulation but there is no support for the conventional transport planning practice of a relatively low interchange penalty with premium weighting of connection time.

Our preference is for a model that increases the interchange penalty by 75%, retains the current frequency penalties and retains a connection time weight of one. It has a LR GJT elasticity of -1.08. Indeed, a revised GJT elasticity similar to this was subsequently adopted by the industry.

Thirdly, we considered whether it would be appropriate to adopt a different model formulation other than GJT and Fare separately. When we examine combining Fare and GJT into a single index, Generalised Cost (GC), the lower fit is evidence that the conventional GC approach is inferior to the GJT and fare approach adopted in the railway industry. Moreover, the implied GJT and fare elasticities are very sensitive to whether the value of time used in constructing GC is based on best evidence or is freely estimated. When we consider dispensing with an index function altogether, via the estimation of separate elasticities to the components of GC, we find this does fit the data better. However, this needs to be investigated further before making any definitive recommendations, and in particular the precise functional form of the component terms and interactions with distance need to be tested given the great flexibility and thus model form possibilities separate components permit.

Therefore, overall, this paper has shown that the GJT index still has merit within the rail demand forecasting setting. However the weighting on the number of interchanges should be increased. This is in order to reflect the greater importance of this factor relative to other timetable service quality factors by service users that is implied by our analysis. Thus we find that the removal of the need to interchange can provide substantial increases in rail demand, over and above what is currently implied by PDFH the forecasting framework.

Finally, the question naturally arises as to the transferability of the method used and the results here obtained to the understanding of rail demand in other countries.

On the first point, the method is entirely dependent upon the availability of a time-series of patronage data along with data relating to timetable related service quality and other relevant explanatory variables. Numerous studies yielding important insights over many years in Great Britain (ATOC, 2013), including many papers in leading international journals, is testimony to the value of such data. Where such data already exists, there is no reason why analysis of it along the lines reported here should not be undertaken Where such patronage data is not routinely available, we recommend that consideration is given by railway organisations to put in place the recording of ticket sales to enable, in due course, analysis of potentially considerable value.

On the second point, it is customary where there is a dearth of ‘local’ evidence to look elsewhere for an evidence base for decision making. More generally, findings from other contexts can serve a useful benchmarking purpose for emerging local findings. We see no reason why the results reported here cannot be transferred to similar countries and contexts elsewhere.

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