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Estimating the impact of new rail station openings on through-passenger demand: a difference-in-differences approach

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Abstract
When a new rail station is built on an existing line, it causes an increase in in-vehicle time – typically, between 2 and 4 min – for all existing trips that now stop at the new station. To the best of our knowledge, this paper is the first to investigate the impacts of these small time penalties on through-passenger demand. Cost-benefit appraisals of new stations in the UK have proven highly sensitive to the forecasts of through-passenger demand reductions. We conduct an ex-post analysis of the effect of a new station on through-passenger demand using a Difference-in-Differences approach. We fail to find a statistically significant impact of the station opening on through-passenger demand. If there are such demand impacts, our findings suggest that these are smaller in magnitude than the standard forecasting approach implies. More research is recommended to corroborate and generalise the findings to other contexts, as these have important implications for the planning and appraisal of new stations.

Keywords Rail demand · Station openings · Small time savings · Rail appraisal · Ex-post evaluation

Introduction

The opening of a new rail station on an existing line imposes an additional in-vehicle time costs for all passengers on existing flows whose journeys now include a stop at the new station. We henceforth refer to these passengers as 'through-passengers'. This paper is concerned with the following question: what is the impact of this small time penalty on the travel demand for through-passengers? Consumer theory would tell us that, even with a small travel time increase, we should expect a proportionate demand reduction (Ben-Akiva and Lerman 1985). Consequently, the application of standard demand forecasting models in

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transport would predict that a new station would lead to a reduction on through-passenger trips. In some cases, depending on the demand elasticities on journey time, these can predict arguably large patronage reductions. This is a particular case of the more general issue of small travel time changes in appraisal, relevant to any transport mode.

At first sight, this may seem an innocuous issue. However, the evidence from appraisal practice tells us the contrary, providing the motivation for this paper. The estimated through-passenger demand reductions can undermine some proposals for a new station, as observed in a recent review of rail appraisals in the UK (Ojeda-Cabral et al. 2023). The review illustrated the severity of the issue with a real example. This was the case of a new train station being planned, which would cause a 2-minute penalty to through-passengers. Its appraisal resulted in a Benefit-Cost Ratio (BCR)[1] of 1.1. However, analysts realised that the BCR was extremely sensitive to one single aspect of the appraisal – namely, the modelled reductions in through-passenger demand – and ran sensitivity tests. If the modelled through-passenger demand reductions were halved, the BCR jumped to 18. If analysts disregarded the through-passenger demand reductions, the BCR became negative due to revenues exceeding the costs of the scheme.[2] This is a remarkable level of sensitivity. But while intuition from analysts and decision-makers suggested that the original model outcomes (i.e. BCR = 1.1) were not realistic – e.g. due to how alternative modes are in that corridor, in particular due to levels of road congestion – and might not be believed, there was no evidence to justify adjustments.[3] Unfortunately, the issue of through-passenger responses to small journey time increases has received no attention in the literature. To the best of our knowledge, this would be the first academic article to expose the relevance of through-passenger demand for new station appraisals. While there is body of literature on the topic of small time savings, the focus has been on valuation using Stated Preferences (SP) (Dubernet 2019; Daly et al. 2014) and its implications for appraisal (Welch and Williams 1997; Bates and Whelan 2001), but not on demand forecasting. The broader issue of non-linear relationships between travel time and demand has also been studied (e.g. Balcombe et al. 2004; Heggie 1976), but existing work is limited and mostly dated. From a demand analysis perspective, the relevant question is whether journey time elasticities are lower for small time changes. Only Wheat and Wardman (2017) and a recent unpublished industry report (The Railway Consultancy et al. 2024) explore such question, with inconclusive results.

Against this background, this paper is the first to explore this question by means of a case study approach. A recent UK station opening provides a controlled quasi-experimental setup. We undertake an ex-post analysis of ticket sales data, using Difference-in-Differences (DiD) techniques, and set to answer the following questions:

- Does a station opening affect demand on flows for which it only increases in-vehicle time by a few minutes?
- How do the estimated demand effects compare to predictions derived using Great Brit-

[1] The BCR is one of the key metrics of a Cost-Benefit Analysis. It is a ratio of the present value of benefits to the present value of costs, measured over the appraisal period (Department for Transport 2025)

[2] In UK appraisals, revenues are treated as a negative cost – not a benefit – and thus appear in the BCR denominator, which turns negative when revenues exceed construction and operating costs. Therefore, such an outcome is even better than a very high BCR.

[3] To clarify, the sensitivity tests retained the disbenefits of 2-minute losses to through-passengers who would continue to travel. In other words, the extreme sensitivity of the BCR was linked only to the modelled demand reductions, mainly via lost revenues.

ain railway industry standard elasticities? (as set out in the Passenger Demand Forecasting Handbook (PDFH) (Passenger Demand Forecasting Council 2018))

This paper aims to provide initial critical evidence for the planning and appraisal of new stations and to position the practical problem of "through-passengers" in the academic literature. In doing so, the paper also makes a novel contribution to the literature concerned with the wider issue of small journey time changes and heterogeneity in demand elasticities. The problem of small time changes has been around since at least the 1970s and poses significant, unresolved, questions for the ranking and selection of different project/policy types by different modes. However, there are gaps in this literature in addition to the aforementioned lack of focus on patronage analysis. Daly et al. (2014) argue for the use of Revealed Preference (RP) data given the perceived challenges with SP data on this topic. Jennings and Sharp (1976) highlight how the arguments for and against a special treatment of small changes may or may not apply depending on the context or scheme type. Yet, the academic literature has steered away from analysing particular interventions. This paper addresses these gaps.

The paper is structured as follows. Section 2 reviews the relevant literature strands. Sections 3 and 4 introduce respectively the data and the case study prior to describing the methodology in Section 5. Section 6 presents the results, with a discussion in Section 7. Section 8 concludes.

Literature review

Rail demand elasticities

Demand studies of new rail stations (e.g. Preston (1991); Blainey (2009); Sperry and Dye (2020)) have covered the new station patronage and station choice, including demand abstraction from nearby stations, but not the issue of impacts on through-passenger trips. This particular topic was flagged, but not explored, by Ojeda-Cabral et al. (2023) in a review of rail appraisals in the UK.

Wardman (2022) provides the most up-to-date review and meta-analysis of travel time elasticities, covering 741 elasticities from 102 studies in Britain. This extends and updates the previous review (Wardman 2012). These reviews note that the evidence base for time-based elasticities is significantly less than for price elasticities. The possible variation of time elasticities with the size of a Generalised Journey Time (GJT) change was not covered.[4]

Wheat and Wardman (2017) were the first, to our knowledge, to study whether GJT elasticities vary with the size of GJT change and with the sign (a reduction vs. an increase in GJT). They found statistically significant effects, indicating that a small change in GJT is linked with a smaller elasticity.[5] However, the effect barely had an influence in the resulting

[4] Rail demand studies typically use GJT, which is a more comprehensive measure of the total journey time between two points, including not only the time spent on the vehicle – as per the timetable – but also other components such as waiting time, frequency or interchanges.

[5] Since elasticities are negative, to avoid confusion we refer to ‘smaller’ or ‘larger’ in absolute terms; thus, a smaller elasticity indicates a less sensitive demand response.

elasticities and the authors concluded that there was no evidence to depart from a constant elasticity.

A more recent industry report (The Railway Consultancy et al. 2024) found mixed evidence in relation to the size of GJT change: “There is evidence that the size of GJT can have an increasing or decreasing impact on the GJT elasticity, depending on segment. This does not seem to have a pattern related to whether the flow is a London flow or whether it is Season or non-Season” (p.80). When the analysis combined all segments,[6] results showed some support for the hypothesis of a less responsive demand to small changes: “Whilst the impact of the size of change appears to be statistically significant and negative (so a larger change implies a greater (negative) elasticity), in reality the magnitude is very small” (p.123). However, and in line with Wheat and Wardman (2017), this impact was too small to have a notable impact on the average elasticity. Both studies had, nonetheless, a much broader scope than ours – e.g. the estimation of a wide range of elasticities for industry-wide use. Thus, the issue of GJT size variation was just one of many. Arguably, this broader scope did not provide a sufficiently controlled environment to examine the issue in isolation.

Another relevant finding, in both studies, is that a time loss (i.e. a GJT loss) is associated with a larger elasticity compared to a time gain, in line with common behavioural economics findings. This finding suggests that GJT losses may be linked with larger than average demand responses, which is relevant for our study.

Finally, the review by Balcombe et al. (2004) highlights relevant evidence from the bus sector: York (1996) and Daugherty et al. (1999) studied the demand impacts of bus priority schemes, finding limited demand impact (in some cases, no impact) arguably because this type of projects cause small time savings that may not be perceived.

Small GJT changes

In the context of the value of travel time savings (VTT), there is a body of literature that has explored whether VTT differs with the size of the time saving. It is a common finding that the VTT increases with the size of time change (Hjorth and Fosgerau 2012), including in the latest national VTT study in the UK (Batley et al. 2019). Dubernet (2019) and Daly et al. (2014) provide reviews of the topic, covering evidence and treatment in appraisals worldwide. The evidence is strong and suggests large variations in VTT with size, “large enough to be of considerable economic significance” (Hjorth and Fosgerau 2012, p. 917). Low or even negligible values for changes up to 5 min are commonly found (Daly et al. 2014). The concern, from an appraisal perspective, is that transport projects (e.g. road schemes) often make up their majority of benefits from the accumulation of small time savings (Welch and Williams 1997).

While appraisal systems of many countries acknowledge this evidence, the convention seems to be to use a constant unit VTT on pragmatic grounds (with a few exceptions). The constant unit VTT convention is primarily driven by the “adding-up” argument (Jennings and Sharp 1976): if a lower VTT was applied to small time changes, the appraisal of cumulative small projects would be different (underestimated) than if they are grouped as one large project. Nonetheless, some appraisal guidelines (e.g. UK and EU) require separate

[6] Rail demand data was analysed separately by segments, as there are clearly different sub-markets by geography (e.g. London) or type of trip (e.g. short distance vs long-distance)

reporting of benefits due to small time savings - lower than 3 (EU) and lower than 2 and 5 min (UK). Also, there is no consensus on what threshold determines a change as ‘small’.

Germany and Canada are the exceptions to the norm (Dubernet, 2019). German appraisal guidelines recommend the use of a smaller unit value (30 per cent reduction) for savings below a 5 min threshold (BVU et al., 2016). Canada does not use a smaller value, but instead directly eliminates small savings (below 5 min) from appraisal calculations – small savings are reported as a separate factor to decision-makers (Transport Canada 1994). In Australia, this topic was revisited in 2011 with the conclusion that there were no sufficient grounds to depart from a constant unit VTT.[7]

From the 1970 s, some authors have argued in favour of constant unit VTT building upon the adding-up argument (e.g. Fowkes 2010), on the basis that appraisals are undertaken over a very long term (e.g. 60 years in the UK): “What matters for a traveller in 50 years time are the travel times in 50 years time, not whether they have come about through a lot of small improvements or one large one. Similarly, it does not matter whether there have been “gains” and “losses” along the way. The traveller in 50 years time will know nothing of travel conditions prior to the scheme or in most of the decades between” (p.25).

On the other hand, Jennings and Sharp (1976) argue that, in some contexts such as short-distance commuter urban routes, the scope for generating and aggregating multiple small time savings over the long term is fairly limited and a lower unit VTT would be justified. Welch and Williams (1997) provide a fuller discussion of arguments on both sides and demonstrate empirically the “very large” potential impact of how small changes are valued, with transport CBA being often “dominated by the economics of small travel time savings” (p.252).

If people value a small time change at a lower unit rate, it would be expected that they also respond to such changes accordingly in their travel behaviour. Thus, the above evidence would support the hypothesis that passengers could be less sensitive to small time changes. If they are, the implications for appraisal practice would need to be revisited and might bring other nuances, since arguments may differ in a context of forecasting demand as noted by Daly et al. (2014). Do the ‘adding-up’ and long-term arguments hold? Ultimately, the questions of valuation and forecasting are closely interlinked, but also pose distinct challenges. Through-passengers who do not stop travelling have to endure an extra 2-minutes, and the valuation debate is concerned with whether we should value them at the standard rate. On the other hand, how many passengers stop (or not) travelling is a matter of factual observation, and it would be incorrect to over-predict large revenue reductions and additional road-related externality disbenefits if these do not eventually occur.[8]

Forecasting framework in Great Britain

The forecasting of passenger rail demand in Great Britain typically follows an elasticity-based framework outlined in the Passenger Demand Forecasting Handbook (PDFH). In simple terms, the approach taken is to multiply existing flow-level demand – measured as

[7] https://www.atap.gov.au/parameter-values/road-transport/3-travel-time.

[8] Note that in any new station case we expect both – valuation and forecasting – questions to emerge. This paper is concerned with the forecasting question, where the evidence is lacking. Further work should explore the relationship in applied appraisal practice between the two.

passenger journeys, though actually a measure of ticket sales – by the growth factors of a set of demand drivers raised to the power of their corresponding elasticities, such that

$$Q_{D,t+1} = Q_{D,t} \prod_i \left(\frac{x_{i,t+1}}{x_{i,t}} \right)^{\beta_i}, \tag{1}$$

where Q_D is rail demand, x_i and β_i are the i^{th} demand driver and its elasticity, and t denotes the time period – typically a given year, since the forecasting and modelling are usually undertaken on an annual basis, using annual data. PDFH sets out the demand drivers and elasticities to be used for a given flow and ticket type. Demand drivers include fare – actually average revenue yield – and a measure of generalised journey time (GJT), along with measures of reliability and relevant 'external factors' (station catchment population, income, employment, etc.). For example, the recommended elasticity of demand with respect to GJT for full fare tickets on a regional flow is -1.1. To forecast the impact of a 10% increase in GJT resulting from a station opening on such a flow, we could make the following calculation:

$$\Delta\% Q_D \approx -1.1 \times 10\% \approx -11\%. \tag{2}$$

PDFH recommendations on relevant demand drivers and their elasticities draw upon evidence from rail demand studies undertaken over several decades. These studies generally involve the estimation of log-linear demand functions of the form

$$\ln Q_{Dit} = \beta_0 + \beta_1 \ln Fare_{it} + \beta_2 \ln GJT_{it} + \ldots + \varepsilon_{it}, \tag{3}$$

Where *i* and *t* denote flows and years, respectively, and ε is an error term. In addition to this idiosyncratic error, models commonly include flow-level fixed effects in order to control for time-invariant flow-level heterogeneity, and year fixed effects or a time trend. The log-linear functional form ensures that our coefficients may be interpreted as elasticities of demand with respect to fare (β_1), GJT (β_2) and so on. Note that the functional form of Eq. 3 imposes the assumption of constant elasticities, though it is in principle possible to deviate from this assumption via simple changes in functional forms, e.g. estimating semi-elasticities rather than elasticities, or adding in second-order terms.

Sometimes, specific parameters are provided where analysis segmentation is possible (e.g. by purpose or journey length). However, GJT elasticities do not vary with the size of the travel time change – although PDFH acknowledges that larger GJT changes might be associated with larger elasticities.

Through-passengers: may we expect a less responsive demand?

Of course, it would not be surprising to find a demand reduction following an increase in travel time. However, we hypothesise that, in the case of through-passenger flows and small time penalties, the observed demand reductions could be significantly lower than what standard models predict, for a number of reasons. First, there is widespread evidence that small time changes are valued at a lower rate (Daly et al. 2014), which would support a lower than proportionate demand response relative to average elasticities. Related to this evidence is the idea that small amounts of time are less useful (Welch and Williams 1997) and/or the possibility that people perceive thresholds and pay little attention to variations within a threshold (Heggie 1976). Second, travel choices are not the 'continuum' that is typically assumed, as in reality people may be restricted to a maximum of two or three differentiated options among rail, bus and car. Since people form habits, it is possible that a small change to their preferred option is not sufficient to trigger a behaviour change. This can be exacerbated in cases where road alternatives are particularly uncompetitive relative to rail. Third, especially for short rail journeys, it is possible that passengers value positively a slightly longer journey if it allows them to use their overall journey time more productively or to relax (Lyons et al. 2007; Blainey 2009; Redmond and Mohktarian 2001) – although it is also true that a few minutes on a short journey may be more noticeable than on a long journey. For these reasons, we also hypothesise that it might be possible that no demand reductions occur at all in the short-term, against the logic of standard consumer theory.

Data

For any given new station opening, only specific flows are directly affected. Analysis of the impact of station openings on through-passenger demand therefore requires the use of flow-level demand data. A Difference-in-Differences approach requires such flow-level data for two kinds of flows:

- *Treatment flows* – flows which involve passing through the new station(s), for which the opening of the new station(s) had some discernible impact on journey times.
- *Control flows* – flows which do not involve passing through the new station(s) but are in other respects comparable to the treatment flows. For example, unaffected flows on the same line or on similar nearby lines, showing similar demand trends to the treatment flows (prior to the new station opening).

We use calendar weekly, flow-level, data on the number of passenger journeys, and on GJT and its components. These are taken from RIDEA (Rail Industry Dataset for Econometric Analysis), a new dataset that provides higher-frequency data on demand, GJT, and external factors than the annual RUDD (Rail Usage and Demand Drivers) dataset used by the majority of existing econometric studies of rail demand in Great Britain. Both datasets ultimately derive their demand data from the official national rail ticket sales database (known as LENNON[9]), and their GJT measures from MOIRA (a UK rail industry modelling tool for rail demand and revenues at OD flow level).

The GJT includes the following components: in-vehicle time (IVT), frequency/headway and, where applicable, an interchange penalty. Thus, GJT data is used to identify the impacts of station openings on treatment flow IVT and to detect cases where nothing else (other than IVT) changes. The GJT data can also be used to calculate the resulting demand impacts as implied by the industry standard demand forecasting methods (PDFH), providing a useful benchmark prior to our econometric estimations. Data on passenger journeys are also

[9] Latest Earnings Networked Nationally OverNight.

broken down by ticket type, and are used as our measure of demand in our Difference-in-Differences models.

The use of the higher-frequency data in RIDEA offers a number of advantages in this context. First, since station openings have taken place at various times of year, their impact on demand would be difficult to discern using only annual data. The use of weekly data allows us to map the periods before and after an opening to the weekly demand data with a high degree of accuracy.

Second, using high-frequency data allows us to more easily disentangle any immediate impacts of station openings from the confounding influence of annual fare changes, semi-annual timetable changes, and the effects of external factors (which over the course of a few weeks should remain relatively stable). This permits visual inspection of any obvious immediate demand impacts in the weeks following a station opening.

Third, since RIDEA includes timetabled GJT data relating to both the summer and winter timetables – in contrast to RUDD which uses only the summer timetable data – we should be able to identify the changes in IVT attributable to a station opening.

Case study

Careful case study selection is essential to try to study in isolation the effects of just a small time penalty. For a given new station, the initial aim is to identify a set of flows that were affected by its introduction in the form of a time penalty. These are the so-called 'through-passenger' flows. Flows involving close adjacent stations, where demand abstraction was likely, were avoided, since demand reductions would be expected primarily due to station substitution.

As our search for case studies confirmed, new station openings often coincide with other changes, e.g. changes to routes, service frequencies, and rolling stock. Sometimes, direct services are retained (effectively avoiding the time penalty for many through services).

Due to data availability, and the need to avoid the exceptional impacts of Covid-19, the search was restricted to the period between 2015 and 2018, when 24 new stations were opened in the UK. Of these, we initially identified a subset of 7 new station openings potentially suitable for our study. This subset filtered out new stations from new branch lines (no through-passengers affected) and the most 'noisy' or complex cases involving multiple simultaneous changes. However, even this pre-selected subset did not fully avoid the presence of simultaneous changes, retention of direct services and stations which are part of complex network/service patterns.

After further exploration, it became clearer that only 3 out of these 7 stations provided an adequate context to study the impact of a small time penalty in isolation: Maghull North, Coventry Arena and Bermuda Park. Since the last two are part of the same line and opened at the same time, this reduced the number of case studies to two. In-depth analysis of these two cases, with the assistance of rail industry partners, revealed that 1 of the cases (Maghull North) provided the exceptionally clean context that we were looking for. That is, the changes in IVT were clear-cut and perceivable, no other changes took place, and there was a sufficient number of treatment and control flows that shared a similar trend prior to the opening (including some controls on the same line). Thus, this paper focuses on the analysis of the Maghull North case study.

Maghull North

Maghull North is a station on the Merseyrail Northern Line, on the corridor between Liverpool and Ormskirk. Figure 1 shows the location of the station.

Merseyrail is the name of both a commuter rail network centred on Liverpool and the train operating company that runs its services. The network is operated under a concession agreement with the devolved transport authority Merseytravel, and consists of two electrified, largely self-contained lines: the Northern Line and the Wirral Line. These are operated exclusively by Merseyrail, which does not run services elsewhere on the national network. The Northern Line runs north–south, linking suburban and coastal areas such as

Fig. 1 Maghull North on the Merseyrail Northern Line. Basemap tiles were retrieved from OpenStreetMap (2024) and are used here under the Open Database Licence (ODbL)

Southport, Ormskirk, and Kirkby to central Liverpool via underground stations like Moorfields and Liverpool Central, continuing south to Hunts Cross. A third line, the City Line, is operated by other train operating companies (primarily Northern) and does not feature any Merseyrail-operated services, but it forms part of the wider Merseyrail network in terms of ticketing and public branding.

Maghull North opened in June 2018, with services running typically every 15 min. When it opened, all the affected flows (i.e. origin–destination pairs with services stopping at Maghull North) in the Liverpool Central–Ormskirk branch experienced an increase in journey time of between 1 and 4 min. Figure 2 shows the evolution of GJT and its subcomponents for an example affected flow: Ormskirk to Liverpool, over the sample period. National Location Codes (NLCs) are shown alongside station names for reference. From Figure 2, we can see that GJT and IVT increase by approximately 4 min with the opening of Maghull North – indicated by an event line – and that besides this, there were no other significant changes in GJT or its components during the sample period. Figure 3 shows the weekly passenger journeys under ticket type ‘full fare’ for the same flow. Note that our analysis excludes data during and after the COVID-19 pandemic, as discussed below, and data covering these periods are included in Figures 2 and 3 for illustrative purposes only.

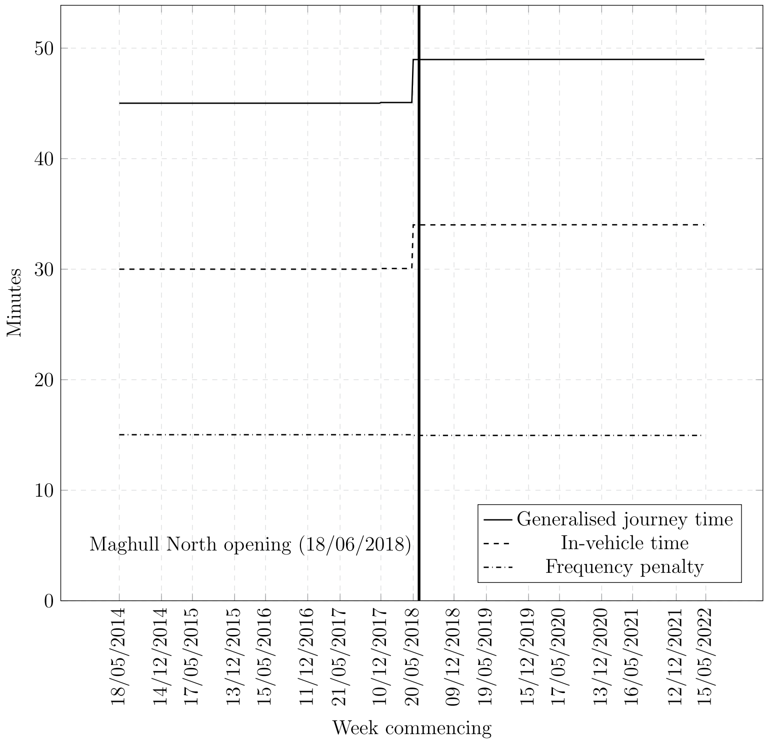


Fig. 2 Generalised journey time and its components, for full fare journeys, from Ormskirk (NLC: 2281) to Liverpool BR (NLC: 0435), by calendar week, w/c. 18/05/2014 to w/c. 08/05/2022. N.B. our GJT data cover every timetable from the 2014 summer timetable, which began in May 2014, to the 2022 summer timetable, which ended in December 2022, inclusive. Dates on the horizontal axis correspond to weeks in which there was a timetable change

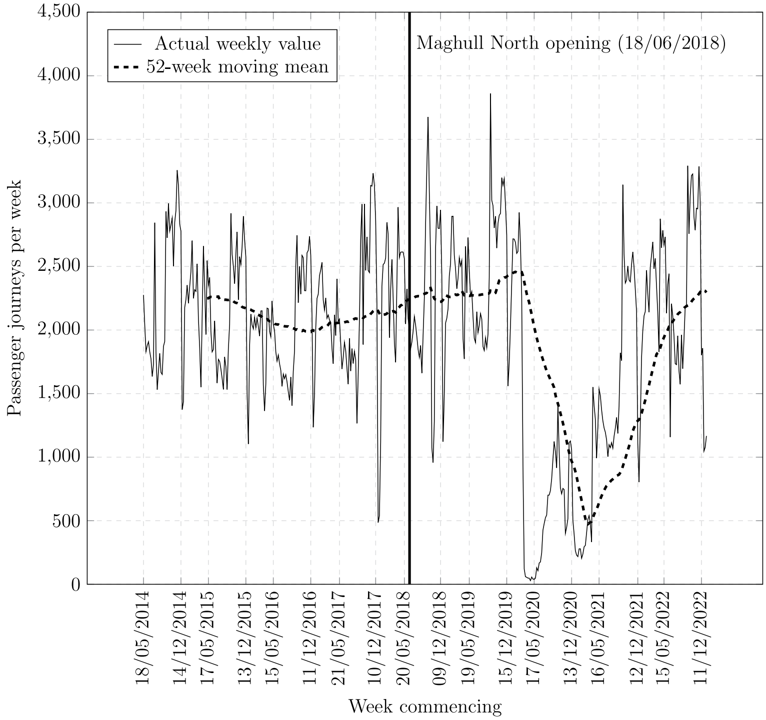


Fig. 3 Weekly full fare passenger journeys from Ormskirk (NLC: 2281) to Liverpool BR (NLC: 0435), by calendar week, w/c. 18/05/2014 to w/c. 08/01/2023. N.B. dates on the horizontal axis correspond to weeks in which there was a timetable change

Table 1 summarises the impact the new station had on GJT and IVT for affected flows. In all, the only change was an increase in IVT, which ranged between 1 and 4 min. The very small divergence between the IVT and the GJT change is due to negligible scheduling alterations that minimally affected the average frequency penalty component of the GJT. Services in the direction of travel towards Liverpool experienced the largest increases. For example, the flow from Ormskirk to Liverpool went from taking 30 min to 34 min. Trains towards Ormskirk had in some cases only 1 min increase, suggesting that the new schedule possibly utilised some of the previously in-built contingency time to accommodate the new station. Frequency did not change and no direct services were retained (i.e. all services stop at Maghull North). The only possible additional change would be an increase in crowding levels. However, this is not a problem for various reasons: available data shows crowding levels were not problematic in this line, the crowding effect would be felt on both treatment and same-line control flows and, relative to other control flows, extra crowding would reinforce the PDFH prediction of decreasing demand (thus placing our results in the conservative side).

As an illustration, the last column of Table 1 shows the predicted reduction in demand if an analyst applied the relevant UK rail industry (PDFH) elasticities (equal to -1.1) to these GJT changes. The most affected flows, i.e. those with increases of 4 min, would be expected to have reduction in demand of around 10 per cent. 2-minute penalties would be associated

Table 1 Changes in full fare journey times on affected flows following the opening of Maghull North (NLC: 6576), and demand impacts implied by PDFH GJT elasticities

Origin		Destination		Δ (Minutes)		%Δ	
Name	NLC	Name	NLC	IVT	GJT	GJT	Q_D
Town Green	2283	Liverpool BR	0435	3.95	3.90	9.73%	−10.70%
Aughton Park	2215	Liverpool BR	0435	3.95	3.89	9.24%	−10.17%
Ormskirk	2281	Liverpool BR	0435	3.95	3.89	8.63%	−9.49%
Ormskirk	2281	Kirkdale	2245	2.92	2.84	7.79%	−8.57%
Ormskirk	2281	Maghull	2155	2.00	1.93	7.60%	−8.35%
Kirkdale	2245	Ormskirk	2281	3.02	2.89	7.49%	−8.24%
Maghull	2155	Ormskirk	2281	2.01	1.91	6.89%	−7.58%
Ormskirk	2281	Old Roan	2258	2.00	1.93	6.79%	−7.47%
Ormskirk	2281	Aintree	2125	2.00	1.93	6.35%	−6.98%
Ormskirk	2281	Orrell Park	2247	2.00	1.93	5.95%	−6.55%
Liverpool BR	0435	Town Green	2283	1.03	0.93	2.26%	−2.49%
Liverpool BR	0435	Ormskirk	2281	1.03	0.93	1.89%	−2.08%

Table 2 Flows included in Case Study – Flows going to Liverpool BR (NLC: 0435)

Origin Station	Origin NLC	Type	Group(s)
Aughton Park	2215	Treatment	–
Ormskirk	2281	Treatment	–
Town Green	2283	Treatment	–
Kirkdale	2245	Control	1
Sandhills	2249	Control	1
Walton	2251	Control	1
Kirkby	2124	Control	2
Blundellsands & Crosby	2123	Control	2
Cressington	2225	Control	2
Hillside	2231	Control	2
St. Michael's	2248	Control	2
Aigburth	2255	Control	2
Southport	2262	Control	2
Ainsdale	2350	Control	2
Freshfield	2355	Control	2

with demand reductions of between 6 and 7 per cent. Note that the PDFH approach implies that demand forecasts are driven by the relative change in GJT. Therefore, the same increase of, say, 4 min, would have a larger demand reduction on a shorter journey (e.g. Town Green-Liverpool vs. Ormskirk-Liverpool).

Unfortunately, demand data were not available for all affected flows. The analysis focuses on three treatment flows in the direction of Liverpool, where data were available. These three flows all experienced an increase of 4 min and had a similar demand pattern in the years prior to the opening. A set of control flows that also share their similar demand trend was selected. Table 2 shows the selected treatment and control flows (see Appendix for a visual display of all flows trends). The control flows are divided into two groups: i) group one includes only flows on the same line; ii) group two includes flows not on the same line but from nearby local stations on similar lines to Liverpool which displayed a similar demand trend pre-opening. Flows on the same line unaffected by the opening are expected

Table 3 Time periods included in Case Study

No.	Description	Weeks included			Obser-
		First (w/c.)	Last (w/c.)	Count	vations
1	Before opening	31/03/2013	17/06/2018	273	4,095
2	1st year post-opening	24/06/2018	16/06/2019	52	780
3	2nd year post-opening pre-COVID period	23/06/2019	23/02/2020	36	540
	Whole sample	31/03/2013	23/02/2020	361	5,415

to be the best control flows, and therefore the models will also be estimated using only group 1 flows as a sensitivity test.

We limit our attention to passenger journeys made using full fare tickets. These are the only data available in RIDEA, and the only flow-level data on demand on the Merseyrail network. Other National Rail ticket types (e.g. season tickets) are not available for most journeys on the network. These are replaced by Merseyrail's Day Saver (unlimited off-peak day ticket) and Railpass (season ticket) products, which are sold outside the National Rail system and therefore not recorded in LENNON.[10]

Given this focus on the full fare ticket types, our data primarily reflect peak-period demand for non-season tickets. Merseyrail's Day Saver tickets are restricted to off-peak use. Nationally, there has been a notable shift away from season tickets toward more flexible or pay-as-you-go ticket types. There is no particular reason to believe that Merseyrail passengers deviate substantially from this national trend, especially given that Merseyrail forms part of the wider National Rail and urban commuting landscape. Most importantly, there is no reason to suspect that these trends differ systematically between our treatment and control flows.

The time periods covered by our data are explained in detail in Table 3. The first period runs from the first calendar week included in RIDEA to the last calendar week before the station opening on 18/06/2018; the second period covers the 52 calendar weeks following the station opening, and the third period runs to the last week beginning in February 2020.

We limit our sample to the pre-pandemic period to avoid confounding effects from COVID-19-related restrictions, which have been long-lasting and geographically uneven. Importantly, we might reasonably expect the effects of the pandemic and various policies enacted to combat it to differ systematically between our treatment and control flows; specifically, our treatment flow origins are outside the Liverpool City Region and thus rail travel into the centre of Liverpool was subject to different local restrictions during COVID-19 tier regulations. Longer-distance travel was also generally more heavily discouraged during the pandemic. While coverage of a longer post-treatment period would be desirable in principle, we judged that the confounding effects introduced by the pandemic and associated restrictions would be impossible to disentangle from any genuine treatment effect.

To summarise, the case study consists of:

[10] While it would, in principle, be of interest to include these Merseyrail products in the analysis, this is made more challenging by the fact that they use a zonal fare structure – similar to that used by Transport for London (TfL) – rather than the flow-level fare structure used by National Rail. It would be difficult, if not impossible, to derive accurate data on flow-level demand and corresponding journey time impacts, given that precise data on usage and on origin and destination stations may not be available.

- A set of treatment flows with GJT (IVT) changes resulting from the opening.
- A set of control flows in the same area (Liverpool) – e.g. on the same line or on comparable nearby lines – which were not impacted by the opening, but are otherwise comparable and shared a similar pre-opening demand trend.

Methodology

We are concerned with estimating the impact of station openings on 'through-passenger' demand on affected flows. Clearly, however, it is inadequate to simply compare demand on these flows before and after the station openings in question. This is because there are many factors influencing rail demand also at work – variation over time in fares, services, seasonal effects, and external factors such as incomes, populations, employment, and so on.

We estimate the effect of the station opening using a Difference-in-Differences (DiD) approach. This method compares the evolution of demand for flows affected by the station (the treatment group) to that for unaffected flows (the control group), before and after the intervention. Provided key assumptions hold, this strategy can isolate the causal effect of the station opening from general time trends.

The DiD estimator is widely used in policy evaluation and applied microeconometrics (e.g., Card and Krueger 1994; Bertrand et al. 2004), and has become increasingly common in transport settings. Applications include congestion charging and traffic safety (Li et al. 2012), infrastructure and house prices (Dubé et al. 2014; Murray and Bardaka 2022), walkability and active ageing (Marquet et al. 2017), and tourism impacts of high-speed rail (Liu 2024).

Identification in a DiD framework rests primarily on the *parallel trends assumption*, i.e. the assumption that, in the absence of the treatment, outcomes in the treatment and control groups would have continued to follow a common trend. This cannot be tested directly, but can be supported by comparison of pre-treatment trends. Violation of this condition can lead to biased estimates (see, e.g., Lechner 2011).

Difference-in-Differences regressions

If we have panel data on multiple treatment and control flows covering periods both before and after a station opening, the change in the control group mean β_1, the initial difference between the treatment and control groups β_2, and the treatment effect β_3 may be estimated using a regression model in which

$$\ln Q_{Dit} = \beta_0 + \beta_1 AFTER_{it} + \beta_2 TREAT_{it} + \beta_3 TREAT_{it} \times AFTER_{it} + \varepsilon_{it} \qquad (4)$$

where *AFTER* is a dummy variable that takes on a value of 0 before the station opening and 1 otherwise, and *TREATMENT* is a dummy variable that takes on a value of 1 for treatment flows and 0 for control flows. Here $\beta_0 = \mu_{C,B}$ is the pre-opening control group mean, and an error term ε is added to capture noise. Ordinary least squares (OLS), under the usual assumptions in addition to that of parallel trends, may be used to obtain unbiased estimates.

In addition to the simple specification outlined in Eq. 4, we estimate a slightly more nuanced model in which

$$\begin{aligned} \ln Q_{Dit} = & \beta_0 + \beta_1 AFTER_{1it} + \beta_2 AFTER_{2it} + \beta_3 TREAT_{it} \\ & + \beta_4 TREAT_{it} \times AFTER_{1it} + \beta_5 TREAT_{it} \times AFTER_{2it} \\ & + \varepsilon_{it} \end{aligned} \tag{5}$$

where $AFTER_1$ and $AFTER_2$ are dummy variables taking on values of 1 in the first and second years after a station reopening, respectively, and 0 otherwise. The reason for this is that the impacts of changes in GJT may be realised progressively. If this is the case, the coefficients on the two interaction terms should pick up distinct demand impacts – more muted in year 1.

Two-way fixed effects difference-in-differences regressions

In addition to the specifications outlined in Section 5.1, we estimate variants of each that include flow-level and time period – i.e. weekly – fixed effects. We cannot, of course, estimate a full set of fixed effects alongside the *TREAT* and *AFTER* dummies, owing to the fact they would be perfectly collinear. In order to avoid this dummy variable trap, we opt to drop the *TREAT* and *AFTER* dummies. Their interaction – the crucial ingredient – remains, however. Eq. 4 then becomes

$$\ln Q_{Dit} = \beta_3 TREAT_{it} \times AFTER_{it} + \alpha_i + \alpha_t + \varepsilon_{it}, \tag{6}$$

and Eq. 5 becomes

$$\begin{aligned} \ln Q_{Dit} = & \beta_4 TREAT_{it} \times AFTER_{1it} + \beta_5 TREAT_{it} \times AFTER_{2it} \\ & + \alpha_i + \alpha_t + \varepsilon_{it}, \end{aligned} \tag{7}$$

where α_i and α_t are flow-level and weekly fixed effects, respectively. This alternative specification controls for any significant flow-level time invariant heterogeneity – due to e.g. differences in origin and destination external factors – as well as general trends and seasonal variation.

These two-way fixed effect (TWFE) models will of course yield exactly the same estimates of the treatment effects as their OLS equivalents. Their standard errors could, however, differ significantly if the fixed effects are significant in explaining variation in demand. Regarding standard errors, in all of our results we report cluster-robust standard errors which account for within-cluster correlation, since this has been shown to be important in DiD settings (Bertrand et al. 2004).

Estimation of percentage changes in demand

We then wish to compare the treatment effect with that implied by UK industry standard (PDFH) GJT elasticities. In log-linear regressions, coefficients on logged continuous independent variables can be interpreted as elasticities, i.e. percentage impacts. A common mistake is to interpret the coefficients of dummy variables in the same way; however, as Halvorsen and Palmquist (1980) note, if β_j is the coefficient on a dummy variable in a log-linear regression, the corresponding percentage impact of the dummy switching from 0 to 1 is given by

$$\delta_j = \exp(\beta_j) - 1. \tag{8}$$

However, simply substituting our estimate $\hat{\beta}_j$ into Eq. 8 yields a biased estimate of δ_j, as noted by Kennedy (1981),[11] who proposed an improved – though still biased – estimator. Giles (1982) derives a series expression for the minimum variance unbiased estimator, $\hat{\delta}_j$. From Theorem 1 of van Garderen and Shah (2002), $\hat{\delta}_j$, and the minimum variance unbiased estimator of the standard error of $\hat{\delta}_j$, are given by

$$\hat{\delta}_j = \exp\left(\hat{\beta}_j\right) {}_0F_1\left(; m; -\frac{m}{2}\widehat{\mathrm{Var}}(\hat{\beta}_j)\right) - 1, \tag{9}$$

$$\widehat{SE}\left(\hat{\delta}_j\right) = \exp\left(\hat{\beta}_j\right)\sqrt{\left({}_0F_1\left(; m; -\frac{m}{2}\widehat{\mathrm{Var}}(\hat{\beta}_j)\right)\right)^2 - {}_0F_1\left(; m; -2m\widehat{\mathrm{Var}}(\hat{\beta}_j)\right)}, \tag{10}$$

where ${}_0F_1\left(; a, z\right)$ is the confluent hypergeometric limit function, $m = (n-k)/2$, $n-k$ is the residual degrees of freedom, and $\widehat{\mathrm{Var}}(\hat{\beta})$ is the estimated variance of $\hat{\beta}$. Eqs. 9 and 10 are used to estimate the percentage impact of treatment, and the standard error of these estimates.

To our knowledge, this issue has not been addressed in the DiD literature, despite the use of log-transformed dependent variables in DiD regressions being commonplace. This issue is not trivial, since the larger the value of $\widehat{SE}\left(\hat{\beta}_j\right)$, the greater the upward bias in the percentage impact implied by the naive plug-in estimator.[12] Despite the applied focus of this study, our highlighting of this issue may be a useful contribution to the DiD literature generally.

Hypothesis testing

Following the estimation of the percentage demand impacts and their standard errors using Eqs. (9) and (10), we conduct hypothesis tests to assess the statistical significance of these impacts. First, we test the null hypothesis that the percentage impact is zero, i.e.,

$$H_0 : \delta_j = 0, \tag{11}$$

against the two-sided alternative

$$H_1 : \delta_j \neq 0. \tag{12}$$

This evaluates whether the estimated demand impact is statistically significantly different from zero.

Second, motivated by the UK Passenger Demand Forecasting Handbook (PDFH) guidance, which suggests a demand impact of around 10%, we perform a one-sided test to

[11] From Jensen's inequality, we can see that the bias is negative, hence this approach would overestimate the magnitude of any demand reduction (or underestimate the magnitude of any demand increase).

[12] This is clearest when we examine the simple bias correction proposed by Kennedy (1981)

assess whether the percentage impact is at least 10%. Specifically, the null and alternative hypotheses are:

$$H_0 : \delta_j \geq 0.10 \quad \text{versus} \quad H_1 : \delta_j < 0.10. \tag{13}$$

This test examines whether the observed treatment effect is statistically significantly smaller than the that which is implied by PDFH guidance.

Results

Tables 4 and 5 report regression outputs for our simpler specifications – including only one post-treatment dummy – and the more detailed model with two separate post-treatment dummies, respectively. In both cases, both OLS and TWFE estimates are shown side-by-side, with the lack of a constant term or coefficients on *AFTER* or the post-treatment dummies in the TWFE cases owing to their being dropped, as discussed in Section 5.2. The models are estimated first using all control flows, and subsequently with only control flows on the same branch line of the treatment flows (group 1 as in Table 2).

Coefficient estimates are reported, with standard errors in parentheses. As discussed, the coefficients of interest are β_3 in Table 4 and β_4 and β_5 in Table 5. These coefficients correspond to the interaction terms between the dummies indicating the treatment group and the post-treatment period(s), and therefore estimate any differential change in the (the logarithm of) demand on treatment flows relative to control flows after the station opening, isolating the treatment effect by controlling for both common time trends and fixed group differences.

As discussed in Section 5, the raw regression results are not themselves the end product, since we must transform the estimated coefficients in order to express them as percentage impacts on demand. Transformed coefficients, interpretable as percentage impacts, are reported in Tables 6 and 7, which show the estimates from the OLS and TWFE models,

Table 4 Maghull North Difference-in-Differences Regressions, Specification 1, Anytime/Peak Tickets

	Dependent variable:			
	$\ln Q_D$			
	All controls		Same branch line	
β_1 $(AFTER)$	0.095^{***}		0.077^{***}	
	(0.023)		(0.009)	
β_2 $(TREAT)$	−0.457		−0.447	
	(0.452)		(0.583)	
β_3 $(TREAT \times AFTER)$	−0.026	−0.026	−0.008	−0.008
	(0.031)	(0.033)	(0.025)	(0.027)
β_0 (Constant)	7.213^{***}		7.202^{***}	
	(0.186)		(0.388)	
Specification	OLS	TWFE	OLS	TWFE
Observations	5,415	5,415	2,166	2,166
R^2	0.072	0.999	0.098	1.000
Adjusted R^2	0.072	0.999	0.096	0.999

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5 Maghull North Difference-in-Differences Regressions, Specification 2, Anytime/Peak Tickets

	Dependent variable:			
	$\ln Q_D$			
	All controls		Same branch line	
β_1 ($AFTER_1$)	0.056**		0.035*	
	(0.025)		(0.021)	
β_2 ($AFTER_2$)	0.152***		0.137***	
	(0.028)		(0.051)	
β_3 ($TREAT$)	−0.457		−0.447	
	(0.452)		(0.584)	
β_4 ($TREAT \times AFTER_1$)	−0.052	−0.052	−0.031	−0.031
	(0.042)	(0.043)	(0.041)	(0.045)
β_5 ($TREAT \times AFTER_2$)	0.010	0.010	0.026	0.026
	(0.029)	(0.030)	(0.051)	(0.056)
β_0 (Constant)	7.213***		7.202***	
	(0.186)		(0.388)	
Specification	OLS	TWFE	OLS	TWFE
Observations	5,415	5,415	2,166	2,166
R^2	0.074	0.999	0.100	1.000
Adjusted R^2	0.073	0.999	0.097	0.999

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6 Maghull North estimated demand impacts, Anytime/Peak tickets, ordinary least squares estimates

	All controls	Same branch line
$\hat{\delta}_3$ ($TREAT \times AFTER$)	$-0.027^{\dagger\dagger\dagger}$	$-0.008^{\dagger\dagger\dagger}$
	(0.031)	(0.031)
$\hat{\delta}_4$ ($TREAT \times AFTER_1$)	−0.051	$-0.032^{\dagger\dagger}$
	(0.039)	(0.04)
$\hat{\delta}_5$ ($TREAT \times AFTER_2$)	$0.01^{\dagger\dagger\dagger}$	$0.025^{\dagger\dagger\dagger}$
	(0.029)	(0.052)
$H_0 : \hat{\delta}_j = 0$	*p<0.1; **p<0.05; ***p<0.01	
$H_0 : \hat{\delta}_j \leq -0.1$	†p<0.1; ††p<0.05; †††p<0.01	

Table 7 Maghull North estimated demand Impacts, Anytime/Peak tickets, two-way fixed effects estimates

	All controls	Same branch line
$\hat{\delta}_3$ ($TREAT \times AFTER$)	$-0.027^{\dagger\dagger}$	$-0.008^{\dagger\dagger\dagger}$
	(0.032)	(0.027)
$\hat{\delta}_4$ ($TREAT \times AFTER_1$)	−0.051	$-0.032^{\dagger}$
	(0.041)	(0.043)
$\hat{\delta}_5$ ($TREAT \times AFTER_2$)	$0.01^{\dagger\dagger\dagger}$	$0.024^{\dagger\dagger}$
	(0.03)	(0.057)
$H_0 : \hat{\delta}_j = 0$	*p<0.1; **p<0.05; ***p<0.01	
$H_0 : \hat{\delta}_j \leq -0.1$	†p<0.1; ††p<0.05; †††p<0.01	

respectively. Also shown are their corresponding standard errors, and symbols indicating the results of two hypothesis tests.

The first test is of the null hypothesis $H_0 : \hat{\delta}_j = 0$, i.e. that the station opening had no impact on demand. The second is a one-sided test, where the null hypothesis is $H_0 : \hat{\delta}_j \leq -0.1$, i.e. that the station opening caused a reduction in demand at least as great as 10%, as implied by the relevant PDFH elasticity. Significance levels for the former test are denoted using stars, while for the latter they are denoted using daggers.

Note that failure to reject no demand impact does not imply that we can reject the null hypothesis of a demand impact in line with the benchmark (PDFH) elasticity – 10% in this case. If the standard errors on these estimates are large enough, it is possible that we fail to reject both null hypotheses – the estimates would be too imprecise to be informative.

In this case, for the simpler model specifications (both OLS and TWFE) – first rows of Tables 6 and 7 – we can see that there are many daggers and no stars next to our estimates. This indicates that we strongly reject the null hypothesis of demand reductions in line with – or greater than – those implied by the relevant PDFH elasticity, while we fail to reject the null hypothesis of no demand impact. In other words, the demand impacts were less than the 10 per cent PDFH would have predicted, and with the possibility that they were actually zero (i.e. no demand impact). When looking at our more detailed models with separate estimates for the first and second years following the station opening, the same results hold for the second-year impacts, but we see that the estimates for the first-year impact are more imprecise: we still cannot reject the null hypothesis of no demand impact, but we can only reject the null hypothesis of demand impacts in line with the PDFH at the 10% confidence level using control group 1 – i.e. control flows on the same branch line as the treatment flows only.[13] In the second year, although not significantly different from zero, the estimated demand impact is positive – the opposite of what we would expect.

Summarising, these results suggest that the opening of Maghull North did not reduce through-passengers' demand as much as industry models (PDFH) would have predicted, and possibly did not reduce demand at all.

Discussion

Let us start by recalling that a GJT increase of 4 min multiplied by PDFH GJT elasticities suggested a 10% reduction in demand for our treatment flows passing through Maghull North. Against this background, our estimates fail to support such a large reduction in peak demand, at least within the first two years following the opening of Maghull North. Indeed, we were also unable to reject the null hypothesis of no demand impact at all.

These findings are aligned with the widespread evidence that people attach low or even negligible value to small time changes (Daly et al. 2014), which can be due to multiple reasons such as perception or usability of small amounts of time (Welch and Williams 1997). Other reasons for these findings may include prevalent passengers' constraints and habits, the uncompetitiveness of other travel modes or even the possibility of positive utility of add-

[13] These results also refute the possibility that some people changed their local station to avoid the increase in rail journey time.

ing a few minutes to a "too-short" rail journey (Redmond and Mohktarian 2001). All these, especially if combined, could explain the observed behavioural response from existing through-passengers in our case study. For instance, between Ormskirk and Liverpool, car journey times are at best 35 min, but roads are highly congested and journeys can actually take 1 h or longer. It would seem plausible that pre-existing rail users were not convinced to switch after their rail journey went up by 4 min – even if they did perceive it.

Before we discuss implications and usability of results, we must acknowledge the limitations. First, we cannot rule out that what we are observing is only a short-term effect. The analysis is restricted to a short-term demand response (2 years after opening). It is possible that the long-run impact takes longer to realise or differs, since short-term mode choices involve different trade-offs than long-term residential choices (e.g. Beck et al. 2017). However, PDFH guidance suggests that for a GJT deterioration approximately 90 per cent of the impact should be realised after a 2-year period. Second, the data on all ticket types was not available, e.g. season tickets. A full dataset would enable a more complete analysis, although the data on full fare tickets does provide significant initial insights with respect to a large market segment. Third, there are other demand drivers which could not be included in the data and might be affected by a new station, such as service reliability (e.g. via changes to dwell times and additional boarding/alighting). For the case where control flows are within the same line, however, there is no reason to suspect that any potential reliability impacts would differ between treatment and controls, which offers some reassurance. Last but not least, the case study approach limits the transferability of results.

Despite these limitations, the quasi-experimental setup is robust and provides us with reliable findings. These findings provide very valuable initial information for the railway industry and community on an important, yet unexplored, issue. Second, our results are also a first step towards addressing key gaps in the literature on small time savings, largely based on hypothetical rather than observed behaviour (Daly et al. 2014).

Our evidence has implications for the appraisal of new rail stations. Recall the motivation for this study: modelled demand reductions of through-passengers can have a large and critical impact on the BCRs for new stations. This evidence provides grounds to begin to challenge the expectation of large demand reductions, while flagging the need for more research. The next step should be to gather more evidence to corroborate and generalise the findings to enable transferability of results, covering other case studies and longer time-frames.

While acknowledging the early nature of these findings, it is worth discussing how appraisal may deal with them. We saw how appraisal practice has largely avoided the use of lower VTT for small time changes, despite the overwhelming evidence (e.g. Dubernet 2019), for reasons such as the 'adding up' argument (Jennings and Sharp 1976). But the debate has focused on 'valuation', not on actual demand responses and 'forecasting'. Demand responses and the associated impacts (e.g. in revenues) are observable facts. If it is observed that demand, and thus revenues, did not drop (or not as much as conventional elasticities would imply), it would simply be incorrect to assume anything different in the appraisal – it is an empirical matter. Unlike the question of which VTT to assign to small changes, which also involves judgement. Suppose that a body of evidence emerged that support lower demand elasticities for small time losses for through-passengers, it would presumably be difficult to argue against their use in appraisal practice.

Some thought may also be given to whether the 'adding-up' argument holds in the case of time losses and new stations. The argument is rooted on the typical case of subsequent road improvements. But, for a given railway line, how likely are continuous subsequent deteriorations in GJT to occur? In the last 25 years in the UK, approximately 100 new stations have opened.[14] It may be possible that a given, say 3-minute, increase is a one-off scenario with no expectation of subsequent increases. And, often, projects and policies move in the opposite direction (i.e. providing GJT reductions). Furthermore, if we consider the case of short-distance routes, the scope for subsequent additions of stations is going to be even more limited. As Jennings and Sharp (1976) pointed out, the validity of the adding-up argument will be context specific.

On the other hand, special treatment of small changes in one forecasting context (new station openings) may be controversial without generalisation to other contexts of small changes (e.g. other rail schemes and other modes), and would require further consideration.

For the time being, while more general evidence is needed, this study certainly warrants more scrutiny around through-passenger impacts. Our study supports the use of sensitivity tests in cases where potential through-passengers demand reductions are likely to act as a barrier to a new station being built. For instance, sensitivity tests halving the modelled reductions could be recommended and given sufficient weight in the decision-making process.

Conclusions

This paper has explored the presumed demand reductions caused by new rail stations on through-passenger flows where a few minutes are added to the timetable. An ex-post analysis of a station opening in the UK was conducted to observe what had happened with through-passenger demand, using DiD econometric techniques. The case study provided a unique opportunity whereby the only effect of the new station on affected flows was a small increase in in-vehicle time (between 1 and 4 min). Nothing else, including frequency, quality or route patterns, changed. No other recent UK stations provided such controlled environment.

The question of rail demand responses to small changes in GJT has received very little attention and the few previous studies were inconclusive. Previous attempts have been only a sub-task of larger demand studies (The Railway Consultancy et al. 2024; Wheat and Wardman 2017) aiming to estimate rail demand elasticities on national datasets – naturally a difficult setting to identify the effect of small time changes due to the many confounding factors. To the best of our knowledge, our study is the first to apply a case study approach and DiD techniques to this question, offering a more controlled environment than previous

[14] https://trundleage.co.uk/reopened-railway-stations/

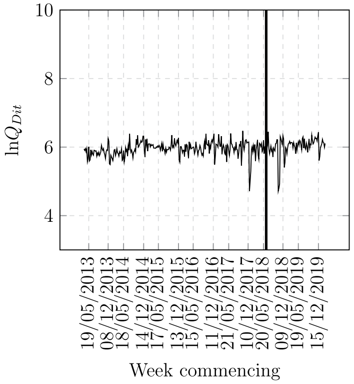
studies. This work also contributes to the literature on the broader issue of small time savings, which has nevertheless focused primarily on whether these are valued at a lower unit rate using stated preference techniques, as opposed to exploring observed demand impacts (Daly et al. 2014).

The key finding of our study is that we could not reject the null hypothesis that no demand impact occurred – i.e. demand response was statistically no different to other similar flows in the same line and same area that were unaffected. This held across the various model specifications tested. We also compared the model estimates with the expected predictions of standard rail forecasting methods in the UK (PDFH), rejecting also the hypothesis that demand impacts were as large as what standard models predict. In other words, our results suggest that the opening of Maghull North did not reduce through-passengers' demand as much as industry standard models would have predicted, and possibly did not reduce demand at all.

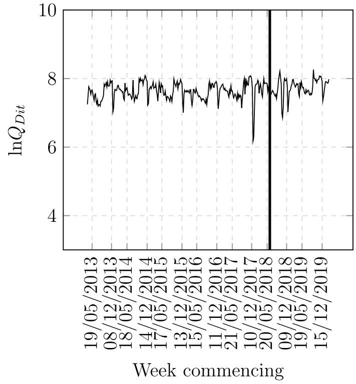
These observations will be of general interest to the railway and transport communities, constitute a novel contribution to the study of "small time changes" and have important implications for the planning and appraisal of new stations – although these need to be threaded carefully as discussed in the paper. In the UK, the forecasts of demand reductions for 'through-passengers' can play a game-changing role in a station Benefit-Cost Ratio (Ojeda-Cabral et al. 2023) and overestimating these could be a barrier to building the station. Given the similarities of appraisal methods in many developed countries (Mackie and Worsley 2013), we hypothesise that this issue extends beyond the UK borders. In Europe, for instance, local communities and authorities are seeking to achieve mode transfer to rail. If our conclusions were to hold, there could be further commercial opportunities for the opening of local rail stations. At the very least, our evidence warrants additional scrutiny around any modelled through-passenger demand reductions from new stations. Perhaps more importantly, it warrants further research to corroborate if the findings hold in other case studies, ideally within a longer-term frame and covering other countries, and in the more general context of small time changes – both in rail and other modes.

Appendix

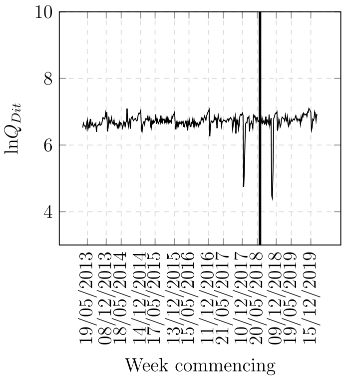
See Fig. 4.



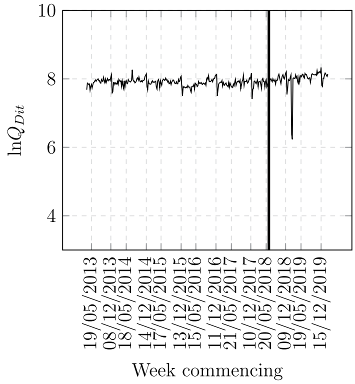
(a) Aughton Park (NLC: 2215) to Liverpool BR (NLC: 0435)



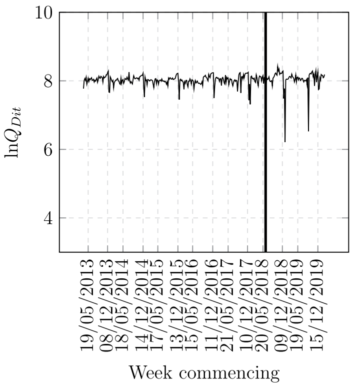
(b) Ormskirk (NLC: 2281) to Liverpool BR (NLC: 0435)



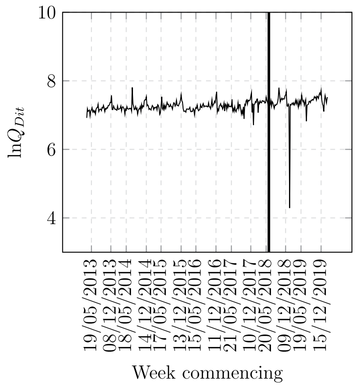
(c) Town Green (NLC: 2283) to Liverpool BR (NLC: 0435)



(d) Kirkdale (NLC: 2245) to Liverpool BR (NLC: 0435)

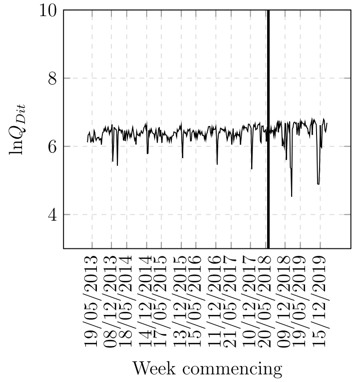


(e) Sandhills (NLC: 2249) to Liverpool BR (NLC: 0435)

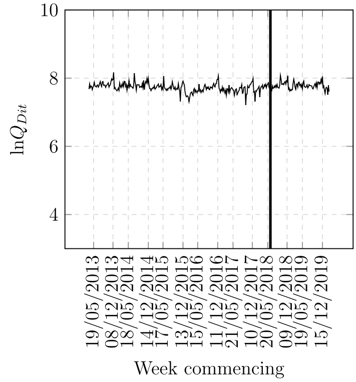


(f) Walton (NLC: 2251) to Liverpool BR (NLC: 0435)

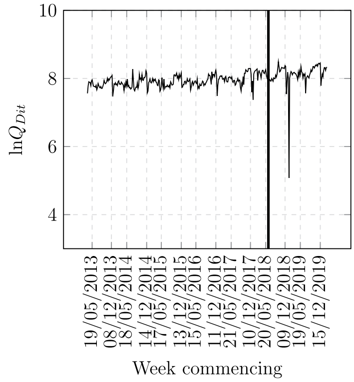
Fig. 4 Natural logarithm of passenger journeys per week, for flows included in the Case Study. The event line denotes the opening of Maghull North (NLC: 2155) on 18/06/2018. Vertical gridlines indicate the dates of timetable changes



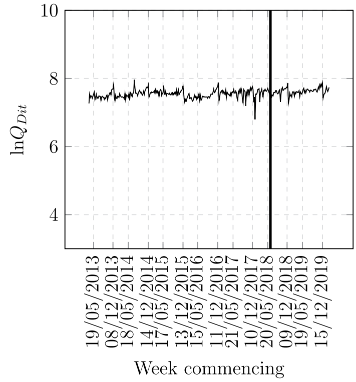
(g) Kirkby (NLC: 2124) to Liverpool BR (NLC: 0435)



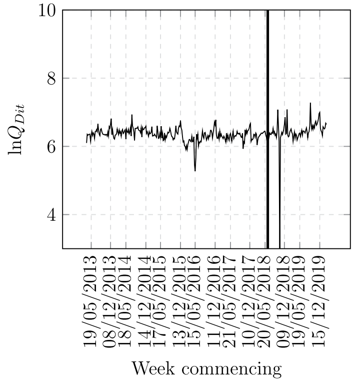
(h) Blundellsands & Crosby (NLC: 2123) to Liverpool BR (NLC: 0435)



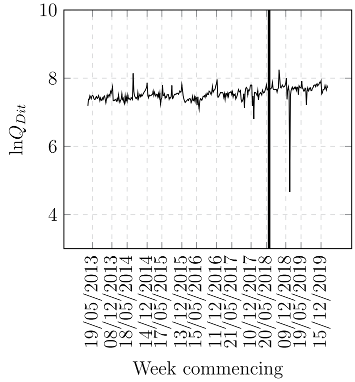
(i) Cressington (NLC: 2225) to Liverpool BR (NLC: 0435)



(j) Hillside (NLC: 2231) to Liverpool BR (NLC: 0435)

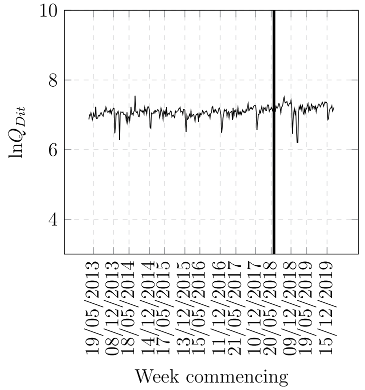


(k) St. Michael's (NLC: 2248) to Liverpool BR (NLC: 0435)

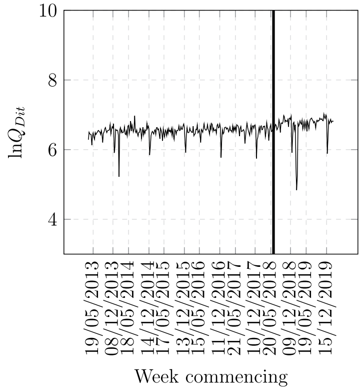


(l) Aigburth (NLC: 2255) to Liverpool BR (NLC: 0435)

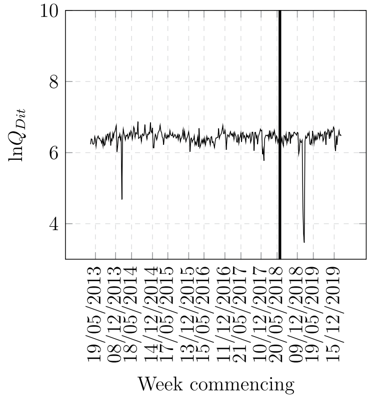
Figure 4 (continued)



(m) Southport (NLC: 2262) to Liverpool BR (NLC: 0435)



(n) Ainsdale (NLC: 2350) to Liverpool BR (NLC: 0435)



(o) Freshfield (NLC: 2355) to Liverpool BR (NLC: 0435)

Figure 4 (continued)

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Author Contributions Manuel Ojeda-Cabral: Conceptualisation, Funding Acquisition, Data Curation, Investigation, Methodology, Writing – original draft, Writing – review and editing. Alexander Stead: Data Curation, Investigation, Methodology, Formal Analysis, Writing – original draft, Writing – review and editing.

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Declarations

Conflict of interest The authors declare no Conflict of interest.

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