VRIJE UNIVERSITEIT AMSTERDAM

SCHOOL OF BUSINESS AND ECONOMICS

Railway Accessibility and Gentrification: A Marginal Approach

Thesis for MSc in Spatial, Transport and Environmental Economics

Matthew Sears (2698829)

Supervised by Thomas de Graaff

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Abstract

Gentrification has become an increasingly popular term amongst academics and activist groups in recent years. As rents and house prices rise in towns and cities globally, the argument proposes that working class, older and ethnic minority residents are priced out at the expense of young, white professionals. In this paper we study how improved railway accessibility fits into the process of gentrification. Anecdotally, the connectivity of an area is an important element in why people choose to live there, ranging from commuting times to access to amenities. Accordingly, we assess whether improved railway accessibility causes or exacerbates the process of gentrification through providing the catalyst for flows of people and capital to move into an area. To test this, we utilise origin-destination flow data from England and Wales between 1999 and 2017. We study whether marginal changes in accessibility, measured as changes in Generalised Journey Time, have an impact on various indicators of gentrification in the immediate area around a railway station. Ultimately we find that the impact of rail accessibility on gentrification is inconclusive. While there is a small positive impact on house prices, changes in demographic factors including the age, employment and ethnicity of residents are either statistically insignificant or inconsistent with what we would expect if gentrification was occurring.

1 Introduction

Public transportation plays a vital role in the economic and social constitution of an area. Improved public transport facilitates higher incomes for individuals and greater efficiency for firms through improved matching between businesses and employees (Chatman and Noland, 2011). This is also particularly important from the perspective of social mobility, as low income residents are less likely to have access to private transport: in the UK, less than half of the poorest 20% of households own a car, compared to over 80% for the rest of the population (National Statistics, 2018). The American Public Transport Agency found a similar result where 57.5% of public transport passengers were from ethnic minorities and 42.4% had no access to alternative private transportation (Pucher and Renne, 2001). Public transport is essential for providing low income households with access to economic opportunities.

Beyond the labour market, public transport serves climate change goals at a local, national and international level. Of global oil demand, passenger vehicles are responsible for approximately a quarter (Kah, 2018). Buses produce half as many emissions as cars. Trains reduce emissions by a factor of 5 (Ritchie, 2020). Transport is responsible for just over 50% of NOx emissions (Inventory, 2020), combined with other particulate matter which contributes to poor local air quality and significant health issues. This all underlines the importance of transferring passengers out of single-person vehicles onto more efficient modes of transport. Beyond the environment, Adler and Van Ommeren (2016) also find that public transport can effectively pay for itself through decongestion benefits.

With particular respect to rail transport, these benefits are being increasingly recognised from a local to a supranational level. The European Union has pledged to treble its high-speed rail network by 2050. The UK has committed to HSII connecting North and South, while China is planning on building an additional 35,000km of high-speed rail by 2035, doubling the length of its network (Chen, 2020). Over the course of the COVID-19 pandemic, the French government pledged to ban domestic flights that could be completed in under two hours by train (Ledsom, 2017. Local governments in the United States are also increasingly recognising the importance of rail transit as a means of channelling investment into urban renewal through Transit Oriented Developments (Cervero, 2004).

This last element of urban development brings together a tension which is increasingly connected both in academia and the public consciousness; that of transport investment and gentrification. An anecdotal description of the gentrification is relatively well understood. Over time both people and capital flow into working class urban areas at the expense of their existing residents. As demand increases, house prices and rents are pushed up causing the displacement of vulnerable residents who are broadly poorer, older and frequently from an ethnic minority background. New residential and commercial developments alter the character of the area, with an increasing proportion of young, middle class professionals and an associated 'boutiqueing' of the shops and services available. A more detailed discussion is provided in the next section, but the stereotypical manifestation of gentrification very much resembles dilapidated family housing being redeveloped into luxury apartments, while ethnic minority food stores are replaced by organic markets.

Gentrification was first academically identified in London in the 1960s (Glass, 1964). However, over the subsequent decades it has been broadly accepted as a global phenomenon. Studies have identified gentrification in the UK (Dutton, 2003); Europe (Nickayin et al., 2020); North America (Slater, 2002); Latin America (Betancur, 2014); and much of the developing world including Indonesia (Prayoga et al., 2013), Nigeria (Nwanna, 2012) and post-Soviet countries such as Georgia (Gentile et al., 2015). The mechanism of gentrification has also spread from focusing on traditional inner-city urban districts to rural towns and villages, including in the UK (Stockdale, 2010), United States (Nelson et al., 2010), Spain (Solana-Solana, 2010) and China (Qian et al., 2013).

While this literature is extensive, the connection between gentrification and transport infrastructure is a relatively recent phenomenon. In many ways this link may seem obvious. Improving the connectivity of a location naturally makes it a more attractive place to live. This subsequently attracts people and capital which catalyses gentrficiation occurring. This paper makes a contribution to this growing literature, ultimately exploring the research question "*how does improved rail accessibility contribute to gentrification*". Bringing together the discussion above, policymakers see an opportunity for urban renewal and upgrading. Rail investment brings social, economic and environmental benefits and can be used to channel investment into deprived areas. On the other hand, existing residents may lose out through increased rents, higher prices and an alien change in the character of a community as the improved accessibility of an area attracts investment and a new demographic of residents. We consider these issues in the context of England and Wales between 1999 and 2017.

This paper proceeds as follows. Section 2 provides an overview of existing literature on the concept of gentrification, and how it links to transport and particularly rail transport. Section 3 then discusses our sources of data and methodological approach, including how we choose to operationalise the concept of gentrification into something we can identify with data. Section 4 provides an overview of our results and in Section 5 we discuss these in more detail with some necessary caveats. Ultimately we conclude that, in line with existing literature, the evidence of rail's contribution to gentrification is mixed. While there may be some increase in house prices, there appears to be no clear and consistent change in the economic or social character of the population. On average, the population may become slightly younger, but this lies in contrast to our other results and we believe is an insufficient condition to conclude gentrification is occurring.

2 Literature Review

2.1 Defining Gentrification

The term gentrification is highly charged, reflecting the contested nature of urban change. On one hand, local politicians and property developers may prefer sanitised terms such as urban renewal or regeneration (Clay, 1979), yet the accusation of gentrification has been used as a motivating force by activist groups from London (Lees and Ferreri, 2016) to Los

Angeles (Huante, 2021), with all the inherent class connotations which it invokes (Lees and White, 2020). The term itself is originally attributed to sociologist Ruth Glass (1964), who described the 'invasion' of gentry into working class areas of London. Multiple occupancy lodgings were converted into "elegant, expensive residences" with "enormously inflated" prices and status. Gradually over time the working class residents are displaced and the character of the area changes out of all recognition.

These processes existed far before Glass' observation. Smith (2005) identifies a kind of proto-gentrification using the example of Baron Haussman in Napoleonic France who was responsible for demolishing swathes of working-class housing to replace them with the grand boulevards which characterise Paris today. While an interesting observation, this bears little resemblance to more modern gentrification which exhibits a relatively common pattern across the 20th Century, particularly in the UK and the United States.

Through the mid-20th Century, the UK and North America were characterised by rapid suburbanisation. A number of explanations have been put forward for this. Hoyt (1939) first proposed a theory of filtering. As the age of housing stock appreciates, owners will invest less due to increasing cost. Eventually wealthier residents choose to move out rather than invest in property upkeep. Rérat and Lees (2011) suggest suburbanisation was encouraged by the "valorization" of suburban living by the state, with the purpose of reducing inner city overcrowding (Clapson, 2003). This was subsequently supported by the proliferation of car ownership, allowing individuals to commute further and benefit through greater separation of work and life (Glaeser and Kahn, 2004). Galster (1990) points to the dynamic of 'white flight' where the racial prejudices of Americans lead them to leave diverse inner-city areas for ethnically homogeneous suburbs. Raban (1974) suggests that the same dynamic occurred in Britain but along class, rather than racial lines. Ultimately dilapidated inner city areas become abandoned by wealthier residents and the political capital that goes alongside them (Boustan and Margo, 2013).

These changes set the foundation for gentrification occurring. Initially a small number of "risk oblivious" people who aspire to live a "nonconformist" lifestyle move into the area with the ambition of renovating their own houses (Lees et al., 2013). This aligns with the stereotype of gentrifying areas being characterised by artists, designers and other creatives. Over time this then attracts small estate agents or speculative developers who may renovate easily procured sites. The scale and visibility of development now occurring subsequently allows media and property developers to rebrand the area as 'up and coming', and ultimately safe enough for middle class residents. This then attracts larger scale developments, alongside greater media and political attention. All through this period, wealthier residents have been moving into the area in increasing numbers (Clay, 1979; Gale, 1979). This raises an interesting contradiction, where there are supposedly negative consequences of wealthier people both leaving and returning to an area. Padeiro (2019) describes this as the "one-two knock" of gentrification where existing residents in a community are abandoned at one time and then ignored at the expense of new residents once investment returns.

This description so far captures gentrification as a process. Originally Glass (1964) focused on the movement of people into an area. Over time new residents move into an area. With some exceptions they are broadly white, wealthy, young, educated and employed in professional occupations (Marcuse, 1985). This may be driven by a rejection of suburban lifestyles (Zuk et al., 2018); a desire to maximize their spatial capital through the convenience of improved proximity to work and amenities (Rérat and Lees, 2011); or simply to benefit from cheaper rent. This can broadly be characterised as the 'demand side' of the process where gentrification is a function of consumer preferences.

More modern studies of gentrification have emphasised the 'supply side' role of capital and public institutions in developing and providing housing and amenities in urban areas. By this theory, gentrifying areas are those which provide developers with the largest "rent gap" (Padeiro et al., 2019) allowing them to charge the highest markup between the cost of what they build and what they can charge in rent. Local governments are often key to this process through approving planning applications. As Zuk (2018) argues, local governments may be biased towards high-value developments to increase property tax revenues. This isn't to say that investment into urban areas is a bad thing. However, for the purpose of this analysis, we will define gentrification as the flow of people and capital into undervalued, predominantly working-class neighbourhoods, causing socioeconomic changes which reflect the priorities of the new residents at the expense of the old.

2.2 Impacts of Gentrification

This then moves the conversation on from gentrification as a process to gentrification as an outcome, that is to say what are the observable changes that enable us to characterise whether gentrification is occurring. These can be broadly grouped into three areas: physical, economic and cultural (Chapple et al., 2017)

One of the most conspicuous outcomes of gentrification is the the physical displacement of existing residents (Rayle, 2015). Over time, the development of an area pushes up rents and forces working class people out of the area. Landlords may increase rents to capitalise on the incoming demographic of wealthier residents, or they may sell properties to developers triggering forced evictions. Simultaneously, the development of an area is likely to push up property prices, meaning lower-income individuals are unable to move in to the area. Not only does the threat of eviction have psychological implications on poorer residents (Twigge-Molecey, 2014), families may be forced to double-up or move in together, causing overcrowding (Zuk et al., 2018). These changes can be observed in increasing house prices, rents and the demographic constitution of an area where the population generally becomes younger, wealthier and whiter.

From an economic perspective the new demographic of residents also changes the demand profile for goods and services in the area. Where there is insufficient commercial capacity, firms compete for floor space causing commercial rents to increase. This generally leads to the closure of shops serving the existing residents, such as food stores dedicated to the tastes of ethnic minorities. Increasing commercial rents are also associated with the closure of small, independent businesses at the expense of chain retailers who have access to more capital (J.-J. Lin and Yang, 2019). Alongside this there may be a growth in 'boutique' stores

(Zukin et al., 2009) where shops specifically cater to the gentrifying demographic, such as offering more expensive organic produce. Accordingly, the increase in rents may either limit the choice of goods for the poorer population, increase the price of what they consume; or price them out of new services entirely.

These economic changes can be simultaneously conceived as cultural, as the kind of shops, restaurants, and social spaces shift away from the existing residents of the area (Lagadic, 2019). A further interesting point is discussed by Chapple & Loukaitou-Sideris (2017) who refer to the commodification of the experience of certain communities while gradually underserving their needs. For example, Lin (2008) argues that the proliferation of Chinatowns in North American cities is increasingly being used as a tourist attraction while simultaneously rents are increasing, and Chinese residents are being priced out of the area.

2.3 Rail Transit and Gentrification

So how does rail transit fit in to these changes? In theory, rail connectivity spans the supply and demand elements of gentrification. Improved connectivity should increase the attractiveness of an area. On the demand side, the young professional demographic is drawn by the improved convenience of the neighbourhood (Rérat and Lees, 2011). Increased demand widens the rent gap, drawing in building developers to construct apartments and commercial space, or to redevelop existing infrastructure. Increased footfall from improved transport links then attracts new retailers to the area with the hope of larger profits.

Measuring indicators of gentrification is typically difficult, and different methodologies are prone to producing different results despite using the same data or the same location (Mujahid et al., 2019). This reflects the fact that much significant research into rail transit and gentrification is inconclusive and contingent on a number of conditions. Existing research also focuses on the impact of new stations opening and the subsequent step-change in network access.

A significant proportion of the research has focused on the impact of new rail transit on house prices, although it appears the house price premium of rail accessibility is highly contingent on the methods employed and the local context. At the lower end of the range of increases, Kahn (2007) uses fixed effects regressions to find house price appreciation of approximately 3% in the mile radius around a station, but only in below median income neighbourhoods, and only if the station is walkable, rather than a park-and-ride. Duncan (2011) uses a hedonic pricing method, finding a higher premium of 11-15%, but similarly only in pedestrian-friendly neighbourhoods. The upper end of the range is around 22% (Bardaka et al., 2018), using a spatial Difference-in-Differences model.

While analysis of house prices consistently finds results, it arguably tells us the least about gentrification. That is to say, house price appreciation is a necessary but not a sufficient condition of gentrification. House prices are increasing globally, but it wouldn't be reasonable to say all such areas are undergoing gentrification. Other housing focused research is less conclusive. Rents do not appear to increase in the proximity to new rail transit (Deka, 2017), although this may be due to housing densification increasing supply (Dong, 2017).

Delmelle, Nilsson and Bryant (2021) find no evidence of increasing rates of evictions near new rail transit stations, or of poorer residents moving out of the area (E. Delmelle and Nilsson, 2020). Housing affordability, measured as the proportion of housing units where rents are greater than 30% of income also doesn't appear to be statistically different in or out of proximity to rail transit.

Evidence of commercial gentrification is similarly mixed. Schuetz (2015) finds no relationship between new rail infrastructure and a change in local employment, but this may disguise the possibility that, for example, independent, ethnic stores and chains would both come under 'retail'. On the other hand, Ong, Pech & Ray (2014) finds that growth in Asian stores near new railway stations was slower than growth across the district, despite higher real estate activity. This suggests that development around railways did not cater to the ethnic minority population. The most comprehensive study is undertaken by Chapple and Loukaitou-Sideris (2017) who explore whether proximity railway stations is associated with increased turnover in commercial establishments, a change in minority-owned establishments, or a shift from independent to chain stores, but finds no relationship between them.

Studies on the changing demographics of an area also find a similarly heterogeneous picture. Various researchers have found evidence of increases in the white population; increasing average incomes; decreasing age profiles; increasing proportions of people in managerial occupations; increase in education levels; increasing car ownership and a variety of other demographic factors which indicate that it is white, middle-class, younger people moving into an area (Atkinson, 2000; Deka, 2017; Dong, 2017; Baker and Lee, 2019; Bardaka et al., 2018; Hess, 2020; E. Delmelle and Nilsson, 2020; Wang et al., 2021). Baker and Lee (2019) provides a composite of many of these elements, constructing a Neighbourhood Change Index, and regressing it against the presence of a railway station in 14 US cities. However, the results vary significantly, with most being statistically insignificant, and the remainder varying from an increase in the index of 27% to a decrease in 37% for census tracts within 0.5 miles of a railway station. Further, while these studies may capture residents moving in to an area, they are unable to capture potential displacement. Hess (2020) finds no evidence of a reduction in the black population around rail transit in Seattle, and Baker and Lee (2019) also find a 3% decrease in the white population around railway stations in Los Angeles. Ultimately the existing research provides a complicated picture of any clear relationship between improved rail transit and gentrification.

2.4 Contribution of This Study

This study contributes to the literature in three ways. Firstly it significantly broadens the geography of how gentrification is analysed. In the first instance, existing studies of transport induced gentrification are focused on the United States. Literature focusing on developing economies is growing but still relatively underexplored, with a similar story true for Europe. The current study corrects for that blindspot by analysing the context of the UK.

This geographical extension also goes beyond the national context of the analysis to the geographical units within those boundaries. Existing literature on transit induced gentrification focuses exclusively on high density urban centres such as Los Angeles (Padeiro et al., 2019), New York (Tehrani et al., 2019), Portland (Dong, 2017), Bangkok (Margono et al., 2020) and Tokyo (J.-J. Lin et al., 2022). However the wider literature on gentrification is beginning to recognise its importance in smaller and more rural geographies such as provincial towns and the commuter belt beyond cities (Stockdale, 2010). This analysis accounts for this shift in focus by utilising the rail transit changes across the full network of England and Wales.

Most importantly, this analysis takes a new approach to analysing the causes of gentrification. As mentioned, existing literature focuses on how indicators respond to the impact of new infrastructure. Intuitively this appears to be for methodological clarity. It is simply much easier to analyse and assess the causal impact of a significant step-change in rail accessibility. However, this arguably overlooks the fact that gentrification is a long-term, marginal process.

The current analysis takes an approach not found elsewhere in the literature. For the purpose of our analysis, we assess how indicators of gentrification respond to marginal improvements in Rail Accessibility, measured as changes in Generalised Journey Time. This provides a number of methodological insights. Firstly, in the context of the UK, the layout of the network is essentially static over time, as only eight new stations have been opened since 2014. Contrary to the focus of other analysis, it is not reasonable to conclude that improved rail transit cannot contribute to gentrification because new areas are not being connected to the rail network for the first time.

Our approach also aligns with a common sense interpretation of the utility of railway travel. It is obviously true that a new station is likely to draw both people and investment into an area, but the same is also likely to be the case for significant journey time savings for commuters. A reduction in journey times from 40 minutes to 30 minutes for a commuter may suddenly make a certain location liveable, and catalyse the same processes of gentrification discussed above. Our approach analyses how indicators of gentrification respond to changes in journey times of railway flows across all of England and Wales. This takes a much more marginal approach to measuring gentrification and also allows us to extend the analysis beyond the urban cores of London, Manchester and Birmingham.

3 Theoretical and Empirical Approach

3.1 Theoretical Background

For the purpose of our analysis we consider how house prices, and demographic factors respond to improvements in Rail Accessibility (RA). However, before doing so it is necessary to condense our method to its core theoretical principles.

The price of a house is a function of its characteristics. This has been discussed at length in hedonic pricing literature, pioneered by Rosen (1974). According to this theory, house prices reflect the quality and number of their intrinsic features, as well as their external access to amenities. We are interested in the second half of this, where transportation access is one feature which may make a house or area attractive. In the same way parents desire to live in areas with good schools (Rothstein, 2006); employees are likely to want to live in areas which are convenient for them to reach their place of work. Through the increased utility of a shorter travel time, the benefits of transport accessibility are effectively capitalised into house prices (Cervero, 2004).

Classical economic theory also proposes that the price of a good or service reflects the Willingness to Pay (WTP) of a consumer. In other words, the price is the maximum a person is willing to pay, and therefore goods are distributed amongst those whose utility will be most satisfied by their purchase. At this point we believe it is worth pointing out the difference between Willingness and Ability to Pay (ATP). As Donaldson (1999) suggests, WTP may be appropriate for comparing consumers with the same income as a means of measuring their preferences. Conversely, the concept is not likely to be appropriate for comparing between income groups.

This is particularly true with the concept of housing. Gentrification describes how incoming residents are wealthier, younger and whiter than their existing counterparts. Strictly following a WTP framework would suggest that white people have a greater preference for transit accessibility than ethnic minorities. Where there is still significant income and wealth disparity between ethnic groups (see Kochhar and Fry, 2014), we don't believe this is a justified conclusion to draw. In this context, a combination of ATP and WTP may be a more reasonable way to conceptualise the demographic constitution of an area. In this sense, the price of housing in an area is as much a function of the income of buyers as their preferences. This provides two ways of understanding demographic changes. As house prices appreciate, people of lower incomes are no longer able to afford a house near to a train station, and so stop moving into the area. They are priced out through their lower ATP. Alternatively, younger people may have a higher preference for accessibility due to the proximity to a more extensive social life elsewhere. Their higher WTP for those benefits may mean they tolerate the higher house prices and mortgage repayments even if they aren't as wealthy as their older counterparts.

Combining these two concepts enables us to conceptualise the process of gentrification in economic terms. An area can simultaneously become younger, wealthier and whiter even with disparities between those categories as it may reflect the WTP or the ATP of those groups. This ultimately means the distinction is purely theoretical. For our analysis we are interested in the outcome, rather than the cause. As house prices appreciate, wealthier residents may move in because of their ability to pay more. Younger residents may move in because of their preferences, and despite of their ability to pay. However, the result of both of these mechanisms is that the demographic makeup of an area may become more homogeneous in response to an improvement in rail accessibility.

3.2 Data

To test these relationships, our analysis relies on three key datasets, which are described below.

3.2.1 Rail Usage and Driver Dataset

The Rail Usage and Driver Dataset (RUDD) keeps a record of journey data for railway travel across England, Wales and Scotland. The data is made up of 24,574 origin-destination flows, with yearly observations from 1995 to 2017. It is worth noting the dataset isn't quite an exhaustive record of rail trips, as 2,247 out of 2,570 stations are included. However the data itself accounts for 90% of journeys and 95% of revenue, indicating that the excluded stations are likely to be infrequently used and insignificant for the analysis.

While the dataset contains over 100 variables, the variable of interest for our analysis is the Generalised Journey Time (GJT). GJT is ultimately a compound measure of the time-based cost of a rail trip. The first element is the Journey Time, itself a combination of the average time waiting for a train, the time spent travelling and any time spent waiting for connections. This cost is then supplemented by Frequency and Interchange Penalties. These are both measures of the relative 'bother' of either waiting for a train or having to change trains. In layman's terms, having a train that regularly departs every 10 minutes causes less frustration than one which operates hourly or half-hourly. Similarly, the annoyance of having to change trains causes a disproportionate hassle to the passenger compared to a direct service (e.g having to move luggage or find a new seat). These measures of hassle are converted into an equivalent time figure i.e. the frustration of having to change trains is equivalent to adding a perceived number of minutes onto the total journey time. GJT is therefore the total of Journey Time, Frequency and Interchange Penalties, outlined in the equation below, where each component is between the Origin and Destination stations:

$$GJT_{OD} = JT_{OD} + FP_{OD} + IP_{OD} \tag{1}$$

GJT is also disaggregated by full, concession and season tickets, reflecting the heterogeneous preferences of different groups of travellers. For the purpose of this analysis we focus on full priced travellers to cover the preferences of the average adult alongside commuters. Alongside this data, RUDD also includes the total number of journeys each year for each flow, disaggregated by ticket type (full, reduced, advance, season, First/Second class), as well as various measures of punctuality for each flow such as the Average Minutes Lateness (AML).

Descriptive statistics for the key transport variables across a selection of years in the panel can be found in Table 1 in Appendix A1. As can be seen, over the time period the mean GJT has reduced from 83 to 78 minutes reflecting improved services across the network. Summary statistics have also been included for the core Journey Time, giving an indicator that the mean time spent travelling makes up approximately 60% of the total GJT. There has also been a significant increase in journeys taken over the period, from just over 45,000 per flow in 1999 to 75,000 per flow in 2015. It is worth noting this is heavily skewed towards certain flows around cities, as evidenced by the large standard deviation.

3.2.2 UK House Price Index

To measure a potential change in house prices, we use data from the Office for National Statistics (ONS) who publish quarterly house price data dating back to September 1995. The datasets available include the mean and median measures of prices as well as the number of sales. For the purpose of this analysis we will use the median measure to account for the highly skewed nature of house prices. The data published by the ONS is available at the level of the Lower Super Output Area (LSOA), the smallest statistical geography in Britain. LSOAs split England and Wales into just under 35,000 parcels. While on the one hand this necessarily means house prices in Scotland are excluded from the analysis, the size of the parcels are generated to be equivalent to populations of 1,500 or 600 households on average, leading to highly granular data (see figure 1 in Appendix A2). Descriptive statistics for the relevant section of the panel can be seen in Table 2 in Appendix A1.

3.2.3 Employment, Age and Ethnicity

As mentioned above, early quantitative studies only focused on house prices as a proxy for gentrification, leading to an incomplete assessment of the issue. Our analysis therefore supplements house price changes with changes to the age, ethnicity and employment profile of residents around train stations. This focus is in part driven by data availability, however it also aligns clearly with the most perceptible features of gentrification where older working class, ethnic minority residents are replaced in an area by younger, white professionals. The following data, summarised in Tables 3-5 for Appendix A1, is all collected by NOMIS, the labour force and population arm of the ONS.

From an employment perspective, we are interested in the occupations of residents who live in the vicinity surrounding train stations. This is collected through the Annual Population Survey which records yearly economic activity down to the LSOA level. Data on employment is then aggregated into nine occupational classifications such as 'Managers and Directors'; 'Administrative and Secretarial'; and 'Process Plant and Machine Operatives' and expressed as a percentage of the total workforce. The occupational categories are described in the next section. As can be seen, the breakdown of employment categories is relatively stable over time. There is a decrease of 4% in the mean proportion of Associate Professional and Technical Occupations and an increase in 2% in the mean proportion of Care and Leisure workers. These are the only notable changes over the period.

Age and ethnicity data is derived from the UK census. As the census is completed every 10 years, this data is only available for 2001 and 2011. Rather inconveniently, the 2021 census has only published indicative data which would be unsuitable for this analysis. It is therefore worth noting that this data is relatively sparse and so any results should be interpreted with such a caveat in mind. While there are yearly age-population estimates available at the LSOA level but these are calculated through extrapolation of the census data and so we don't believe they are likely to add significant explanatory power to the analysis. It is also worth noting at this point that the summary statistics indicate the proportion of some ethnic minorities is so low in some districts that analysis would be unlikely to lead to reliable results.Consequently our subsequent analysis of the ethnic composition of the districts focuses only on changes to the proportion of people identifying as White British.

The data indicates fairly well-known trends in demographic changes. The British population is becoming more diverse, with a decrease in the mean proportion of White British people from 92% to 89%. It is also becoming older, with the mean proportion of those aged 45-64 increasing from 24% to 26% of the population in each LSOA, as well as a small increase of 0.5% for those aged 65+.

3.3 Methodology

Our analysis assesses how house prices and demographic factors respond to changes in Rail Accessibility. This initially requires some reworking of the datasets being used. We begin with the RUDD dataset. As mentioned, this gives a record of the Generalised Journey Time (GJT) for almost 25,000 flows across a 20 year time-period. Many of the flows in the dataset are between small, rural stations with very few journeys taken between them every year. We find that these flows also correlate with smaller levels of housing sales over the time period. Due to these reasons, we believe improvements in the GJT of these minor flows will potentially lead to spurious responses in the housing market, particularly as the house price data is collected from fewer transactions. As a consequence, we made the decision to remove these smaller flows. To do this, we calculated the mean number of journeys for each flow over the time period, and then removed all flows below the median of this figure. If we had simply removed flows below the median of the entire dataset this would not account for flows which had seen significant journey growth over the period. Reducing the size of the dataset by half may seem like a significant reduction, but it is worth noting that this only removed flows which averaged 4,600 journeys per year over the period, or the equivalent of around 13 journeys per day.

While our results could be skewed by smaller flows, we also have to account for the relative importance of flows out of the same origin station. In the UK, Brighton has become a significant origin station for commuters into London. However Brighton is also connected to small towns all along the south coast. In this context, a 1-minute improvement in journey times to London is likely to have a more significant impact on house prices and demographic changes than a 5-minute improvement to stations such as Worthing or Bognor-Regis. To capture this dynamic, we create a variable for Rail Accessibility (RA) which is the flow-GJT weighted by the mean level of employment in the district where the destination station is located.

We are interested in changes to the immediate vicinity around railway stations. The literature generally agrees that the spillover effects of transport infrastructure reach approximately 3-5 km from the access point to the transport mode. To emulate this methodology we use Geographical Information System (GIS) software to create a matrix of the intersection of LSOAs across England and Wales with the origin stations being studied. Due to a lack of computer processing power, the radius extends to 1km around each station. While this is below the boundary often examined in the literature, it still amounts to a dataset of over 11 million observations and is likely to be the area where any changes are most visible. It is also worth noting that since we are using data from the entirety of each LSOA which falls within that radius, this data does effectively extend beyond the 1km boundary. This can be seen in Figure 2 which shows the intersection between the radius around the station and the LSOAs along part of the network between Manchester and Leeds, and how the LSOAs extend beyond the radius boundary.

This ultimately allows us to build our analysis dataset. We focus on changes at the flow origin, that is to say, we are interested in how indicators of gentrification at the traveller's origin are impacted by the ease at which they can reach their destination. It is also worth noting that many of the flows in the RUDD dataset are uni-directional, indicating that they appear twice with each station featuring as an origin and destination. This means we can capture the dynamics at each end of the flow as, for example, people will commute in both directions. Again, these changes are weighted by the number of jobs at each destination. We create our analysis dataset through connecting the flow data to the house price and demographic databases, meaning each flow is linked to a matrix of LSOAs in its vicinity with an associated median house price, age and ethnicity breakdown and proportional breakdown of employment sectors.

3.3.1 Variables

Before turning to our specific empirical specification, it is important to clearly define the variables we are measuring:

Independent Variables As mentioned previously, we are attempting to analyse the impact of a change in Generalised Journey Time (GJT). The GJT is the compound measure of the time-based cost of a rail trip. For each origin-destination flow, this includes the in-train journey time, the time spent waiting for a train and any time waiting for connections. Further multiplier penalties are added for the bother of waiting for a train and having to change trains along the route. For our analysis, we focus on the preferences of full-price travellers, rather than concessions who have slightly different preferences. As mentioned previously, this is weighted by the number of jobs in the destination district. For ease of interpretation we then take the natural log of this figure, and label the final variable Rail Accessibility (RA)

Control Variables A number of control variables are used in the analysis to correct for bias. Local disposable income is used to control for the relative wealth of the area. Gross Value Added (GVA) is in part used to control for economic trends, but also to adjust for changes in house prices as real estate 'productivity' is often used in calculations of GVA. Local car ownership is also added, as areas with low car ownership are likely to be more dependent on public transport so this may have an impact on the outcome variables. Finally we also control for the average train delay over the time period as a measure of service quality. Improvements in journey time may be offset by frequent delay, or perceptions of delay may impact the attractiveness of an area so we control for this.

Dependant Variables Due to the wide range of factors we are looking at, we have a significant number of dependent variables. The variables included in the analysis are as follows:

House Prices:

House price data is published quarterly at the LSOA level:

- The natural log of the median house price, calculated at the LSOA level

Employment:

The following variables are chosen as the most relevant employment categories for indicating the 'professionalisation' of an area as suggested by theories of gentrification. This is provided annually at the LSOA level and averaged over the proportion of each LSOA in a 1km radius around a station:

- Proportion of population employed as "Managers, Directors and Senior Officials"
- Proportion of population employed in "Professional Occupations"
- Proportion of population employed as "Associate Professionals and Technical Occupations"
- Proportion of population employed in "Caring, Leisure and Other Services"
- Proportion of population employed in "Sales and Customer Service"
- Proportion of population employed as "Processing Plant and Machinery Operatives"
- Proportion of population employed in "Elementary Occupations"

Age:

The following variables are calculated yearly and at the LSOA level:

- Proportion of population aged 0-14
- Proportion of population aged 15-29
- Proportion of population aged 30-44
- Proportion of population aged 45-64
- Proportion of population aged 65+

Ethnicity:

- Proportion of population identifying as White British

This variable is included in order to capture how gentrifying areas become more white over time, that is to say that ethnic minorities are priced out of an area. While used in the analysis, it is worth noting that this data is fairly weak. Firstly, it is only collected as part of the UK census conducted every 10 years so it is only available for two years of the time period we are considering. Secondly, to ensure confidentiality, it is only published at the district level, rather than the LSOA level. Therefore we do not anticipate many significant changes when looking at a much larger geographic area.

3.3.2 Hypothesis Testing

Using these variables allows us to formulate some more concrete hypotheses over the changes which may suggest gentrification is occurring. Firstly we anticipate that an improvement in RA will lead to an increase in house prices. Secondly, if gentrification is occurring we would expect a 'proffesionalisation' of the residents of an area. At one end of the spectrum this should show an increase in the proportion of Managers, Directors, Professionals and Associate Professionals. At the other end, we could also anticipate seeing a reduction in the proportion of those employed in Care work, Leisure, Customer Service, Machinery Operatives and those employed in Elementary Occupations.

In line with the theory discussed above, if improved rail accessibility causes gentrification, we can also expect to see a reduction in the age balance of the area. A simple expectation would be to see an increase in the proportion of everyone aged under 65. This would account for young gentrifiers as well as older gentrifiers with children, while older residents may be priced out of the area.

Finally, if gentrification is occurring, we would expect to see an increase in the proportion of the white population. As discussed above, this data is unlikely to be reliable. This is also why we have decided to focus just on changes to the white population, rather than looking at the other nine ethnic categories as well.

3.4 Pooled OLS

As part of our investigatory analysis, we employ a pooled OLS method. Our specification is as follows:

$$\Upsilon_{it} = \beta_0 \ + \ \beta_1 \ \Delta \ RA_{ijt} + \ \beta_2 \chi \ + \ \varepsilon_{it} \tag{2}$$

For simplicity in this specification, Υ can be interpreted as any of our dependent variables i.e. house prices, age or employment variables. Therefore Υ_{it} is the house price in LSOA i in quarter t. χ is a matrix of control variables and $_{it}$ is the exogenous error term.

3.5 Fixed Effects

While a standard pooled OLS approach provides a useful indicator of the range of our results, it is likely that the results are biased. Despite an array of control variables, there is likely to be further omitted variables, including unobserved heterogeneity between the panel variables. To control for this we add entity and time fixed effects to our estimation, represented by α_i and δ_t in the equation below:

$$\Upsilon_{it} = \beta_0 \ + \ \beta_1 \ \Delta \ RA_{ijt-x} + \ \beta_2 \chi \ + \ \alpha_i \ + \delta_t + \ \varepsilon_{it} \tag{3}$$

We are investigating how our dependent variables respond to a change in journey time, represented by $\Delta \ RA_{ijt-x}$. The suffix represents the journey time from a station which intersects with LSOA i, to destination j, with an undefined lagged time variable $t - x$. This illustrates that house price and demographic changes do not occur simultaneously with train time improvements. Demographic changes particularly are slow, so it is likely that any shifts will be observed a number of periods after the RA. To investigate this relationship we test changes lagged over 1, 2 and 3 years respectively.

Our unit of analysis is the Lower Super Output Area, so this is the unit at which we set out entity-based fixed effect. Separately, we also add a time variant fixed effect to control for unobserved time trends in the data. We add these as regional, rather than national level time variant fixed effects. Due to the granularity of the data at the LSOA level, we did not think it was appropriate to assume there are trends that vary over time but do not vary at all between LSOAs. For example, the housing market in the South East of England is very different from rural Wales. We believe this adds a more representative means of controlling for time trends than a national-level effect. All the other variables remain the same.

As part of this step, we also reduce the size of the sample to exclude large cities as origin stations. The logic for this is that it helps to remove an element of reverse causality. It is possible that upgrades to the timetable could be motivated by connecting economic hubs such as London to Birmingham or Manchester to Leeds. To use the previous example, infrastructure work on the line from Brighton to London may be targeted due to the fact Brighton is already in the process of gentrifying, with significant appreciation in house prices. On the other hand, it is less likely that engineers and timetable planners are targeting this work due to house price appreciation at minor stations such as Three Bridges, Wivelsfield or Hassocks. By removing large stations as the flow origin, this reduces the possibility of reverse causality where journey time improvements are targeted where gentrification is already occurring.

3.6 Establishing Causality

While the introduction of fixed effects and removal of large origin stations may improve the reliability of our results, we take two final steps to deal with bias and reverse causality by manipulating the data to replicate a kind of natural experiment.

In an ideal situation, we would look at where there is a single, material step-change in the timetable, similar to existing literature that looks at the opening of a new station. To do this we firstly restrict our analysis to a subsample of the data looking at flows where there were at least 8 consecutive quarters of no changes to the timetable. This gives us a clear observable boundary around which to observe changes in house prices and demographic factors.

We then reinforce the significance of this experiment by further refining our data to look at a large step-change in journey times. We anticipate that passengers are more responsive to larger changes in journey times. For this final step, we then look just at flows around this boundary where there is a change of five minutes or more. We believe that the coefficients for this step are the most likely to represent an unbiased picture of how house prices or demographics respond to noticeable improvements in journey times. The next section provides a chronological walkthrough of our results.

4 Results

This section outlines the results of our estimations, firstly using Pooled OLS, then subsequently adding fixed effects on the whole sample, and finally reducing the sample size to engineer an environment more similar to a natural experiment.

We are assessing how house prices and demographic factors respond to a change in Rail Accessibility. More specifically this is calculated as the generalised journey time, weighted by the volume of employment at the destination station. This requires two important clarifications. Firstly, having an independent variable which is itself a compound of other variables makes interpretation of the coefficient somewhat difficult. For simplicity's sake, we are therefore more interested in the direction of such changes, or whether the coefficient is positive or negative. Accordingly, a negative coefficient indicates an increase in the dependent variable. The sign of the RA variable is dictated by changes in generalised journey time, therefore house prices may increase in response to a decrease in GJT. To word it another way, a reduction in the value of the RA variable indicates an improvement in accessibility.

The second clarification is a reminder that we are looking at RA changes at the flow level. This provides some context to the scale of the coefficients. Any change is in response to RA changes for a particular flow out of the station, rather than an average improvement of the total flows out of that station.

4.1 Pooled OLS

For our first set of results, we estimate equation 1. The full results for our pooled OLS estimation can be seen in Table 6 and Table 7 in Appendix A3. It is worth noting that of the dependent variables, only the coefficient for house prices is as a natural log. These results confirm our predictions in some areas but appear to be counterintuitive in others.

As anticipated, there is a statistically significant relationship between rail accessibility and house prices. This can be interpreted as an elasticity - A 1% increase in rail accessibility of a particular flow leads to an increase in house prices of 0.01%.

On the other hand, the demographic variables provide a mixed group of results. From an employment perspective, it appears as though a 1% increase in RA leads to a 0.00008 percentage point decrease in Managers and Directors, as well as a 0.0002 percentage point decrease in those employed in Professional occupations, as well as a decrease in Associate Professionals. While there may simultaneously be a 0.0004 percentage point decrease in Leisure and Care workers, as well as a 0.0001 percentage point decrease in Machinery and Plant Operatives, this is countered by a 0.0002 percentage point increase in those employed in Elementary Occupations in response to an improvement in RA. This is largely counterintuitive to what we expected.

Despite this, the changes in the age breakdown are consistent with our predictions, that is to say, on average, an improvement in RA correlates with a reduction in the age profile of residents. For those aged between 15 and 45, a 1% increase in RA correlates with a 0.002

and 0.003 percentage point increase in equivalent proportions of the population. For the older segment of the population, a 1% improvement in RA causes an approximate 0.003 percentage point decrease in those aged 45 or above. Our expectations are also met with an apparent decrease in the proportion of the White British population, with an equivalent decrease of 0.0001 percentage points.

However, underpinning all these results is the issue that they're biased. As described in previous sections, they provide some useful indicative analysis as to the scale of the coefficients. However, there are likely to be many unobserved variables, as well as the issue of reverse causality which renders them inaccurate. For example, this could be applied to both house prices, and subsequently the increase in the proportion of residents aged 65+. Railway engineers or governments could be targeting accessibility improvements at areas with high, or growing house prices. In the UK, there is also significant inequality in both wealth and home ownership by age. Therefore if improvements are being targeted at areas with increasing house prices, this would also explain the apparent increase in older populations i.e. that RA improvements are following high house prices and their older homeowners, rather than the other way round. To correct for some of this bias we turn to panel regressions with fixed effects:

4.2 Fixed Effects

To control for unobserved hetereogeneity between geographical units and unobserved time trends, we add both a location and time-based fixed effect to estimate equation 2. As outlined above, unlike pooled OLS we can now also make use of the panel structure of the data. Alongside controlling for fixed effects, this allows us to test the impact of time lags on the results of the regressions. Most obviously, any changes to house prices and demographic factors will not happen simultaneously with RA changes. It may take months for the benefits of improved journey times to capitalise into house prices. Demographic shifts also happen over a longer period of time. For example, it is unlikely that a statistically significant group of young white professionals are watching out for and will be ready to move house even within a couple of months of a timetable improvement coming into effect. Therefore any changes may not be observable for months or years after the change.

The results of these tests can be seen in Tables 8 to 22. With respect to the time lags, we believe that house prices are most responsive to changes in RA. Therefore these regressions are tested at quarterly time lags up to 3 years after the timetable change occurs. Demographic changes are likely to be slower, so these are tested at annual lags up to three years.

Compared to the Pooled OLS results, the impact of RA improvements on house prices is now weaker but also indicates that the impacts are consistent over time. Over the three years following a timetable improvement, there is between a 0.0004% and 0.0005% increase in house prices in response to a 1% improvement in RA. This suggests that the benefits of improved rail accessibility are capitalised into house prices over a fairly long period of time.

The direction of changes to the age constitution of the area is broadly the same as the Pooled OLS estimation, although significantly smaller. A 1% improvement in RA now correlates with a 0.0001 percentage point decrease in 45-64 year-olds and a 0.00009 percentage point decrease in those aged 65+. There are now statistically significant decreases in those aged 0-14 but statistically significant increases of 0.0003 percentage points of those aged 30-44 who the literature suggests are a key gentrifying demographic. Unlike the previous estimation, the change in proportion of White British people is statistically insignificant.

Similar to the Pooled OLS estimation, the impact of improved RA on sectors of employment is mixed. There is a statistically significant decrease of around 0.000008 percentage points of Directors and Senior Officials in response to a 1% improvement in RA. There is also a reported equivalent decrease of 0.0001 percentage points in Associate Professionals. Both of these are the opposite of what we would expect. Similarly, any changes to Professional Occupations, Leisure and Care workers, and those employed in Elementary Occupations are statistically insignificant. There is a decrease in Machinery Operatives of 0.0007 percentage points for the same change in RA, and a 0.0004 percentage points increase in Sales and Customer Service employees.

4.3 'Natural' Experiment

As mentioned above, for our final estimation we restrict the sample size to replicate a natural experiment. To do this, we limit our analysis for flows where there are eight consecutive quarters of no timetable changes, followed by a change of more than five minutes. This creates a hard boundary around which to capture changes, as well as only analysing changes that are large enough to be noticeable by passengers and the population around a station. We believe this is the most likely way to capture a causal relationship between changes in RA and indicators of gentrification. Our analysis also uses the same time-lags as before.

As seen in Table 23, the relationship between RA and house prices is still what we would expect, although now with a different temporal dynamic. According to this estimation, there is now an elasticity of between 0.008% and 0.012% in the first 3 quarters after the timetable change, which then becomes statistically insignificant after a year. This is also significantly larger following the adjustments to the sample than the fixed effects estimation above now we are closer to isolating the causal impact of RA improvements.

The most significant change in this final estimation is to the breakdown of employment characteristics in the radius around a station (Tables 24 to 30). There is now no statistically significant relationship between RA and the proportion of Directors, Professionals or Associate Professionals. Slightly counter to expectations, a 1% improvement in RA now leads to a 0.006 percentage point increase in Sales and Customer Service employees. Alongside these results, there is now no statistically significant decrease in Leisure and Care workers or those in Elementary Occupations. Similar to the previous estimation a 1% improvement in RA leads to a 0.008 percentage point decrease in Machinery and Plant Operatives. The impact and robustness of these results is discussed in the next section.

Our results for the impact of RA on the age constitution of an area are also similar to the previous results but again more significant. An improvement of 1% in RA now leads to approximately a 0.004 percentage point decrease in 0-14, 45-64 year olds and those aged

65+. Conversely, there is a statistically significant increase of 0.006 percentage points of those aged 15-44. This excluding the youngest age bracket who obviously have little to no say in where they live, this result does suggest a reduction in the average age profile of the area. The change in proportion of people identifying as White British was omitted from the regressions as the trends were indistinguishable from the time variant fixed effect.

5 Discussion

Assessing both the positive and negative impacts of improved rail accessibility is important for effective policy-making. Raising the potential negative impacts, of which gentrification is a significant one, can help policy be tailored to mitigate the effects on those who may lose out from such policy. In light of this, our analysis makes a number of contributions to this discussion. In one sense, this analysis is a continuation of existing literature which concludes that assessments of gentrification are somewhat dependent on the context and statistical methods used. However, our analysis also represents a new avenue which assesses how socioeconomic factors respond to marginal improvements in rail accessibility, be that journey times, reduced interchanges, or increased frequency.

This naturally leads on to what conclusions we can reliably draw from our results. Firstly, across our three estimations, we find consistent evidence of house price appreciation. Interestingly, once we reduce the sample size to better isolate a causal impact, the elasticity increases from 0.0005% to around 0.008%, an increase by a factor of around 16. Our final estimation also suggests a temporal dynamic to house price appreciation, where it is visible for the 3 quarters after a timetable change, and then becomes insignificant. A small, short-term appreciation appears intuitively reasonable, however the time dynamic is less certain. While our house price data is published quarterly, the timetable data is only published yearly. However, on the UK rail network, timetable changes occur every six months. This means that the lag between timetable change and house price appreciation has a wider boundary of six months in either direction.

It is also necessary to discuss the economic significance of our results. The most detailed description of our coefficients is how any of the factors responds to a change in the natural logarithm of the flow-level journey time, weighted by the average employment at the destination over the time period in question. Accordingly, interpreting an elasticity of 0.008% becomes somewhat confusing. In a simple sense, we can interpret a direction of travel. This means our results can act as a proof of the mechanism of gentrification, where house prices appreciate as train accessibility improves. Alternatively we can make attempts to estimate changes which are easier to interpret. For example, let us consider the mean values of our variables. The mean value of our RA variable over the time period is approximately 8.5. Additionally, the ratio between our RA variable and the mean flow journey time is about 5.4. Therefore we can assume that our mean RA variable corresponds to a journey time of around 46 minutes. If we then apply this to our coefficients, a 10% improvement in RA (assuming a 1:1 improvement in journey time) would be a journey time reduction of about four and a half minutes. This would then correspond to an increase in 0.08% house prices in the 1km radius around the origin train station. Over the time period, the mean house price is approximately £200,000. This would therefore increase by £160. This calculation ignores the temporal dynamic of the variables in question, as well as the significant amount of geographical variation as properties in the commuter belt around cities are likely to appreciate much more significantly. However from this rough calculation we can conclude the effect is very small.

The impact of improved RA on the age constitution of an area also initially confirms our theories of gentrification, in that the age profile generally becomes a bit younger. An equivalent 10% improvement in RA leads to a 0.04 percentage point decrease in those aged 45-64 and those aged 65+. On the other hand we have an increase of 0.06 percentage points for 15-29 and 30-44 year olds, who are generally more likely to be part of the demographic considered gentrifiers. However, it is also possible to speculate over the validity of these results. One of the key of gentrification is the displacement of older, working class residents. Since the data we are using is based on percentages, we cannot confirm whether this is happening. An increased younger population could be the result of increase housing densification, rather than displacement. There is also the issue in the UK that around three quarters of people aged 65+ own their own home (Cribb et al., 2018). Therefore these are the people that benefit from house price appreciation and there is no clear logic as to why they would be displaced by ongoing gentrification. Therefore it is not particularly clear as to whether we can conclude these changes are definitively gentrification. Our analysis of age changes is also limited by the data availability. At the LSOA level, age data is only available for the census years of 2001 and 2011. This naturally means that the robustness of the data may be undermined as we are looking at a smaller number of data points with significant periods of time between them. As can be seen in Tables 31-35, our analysis is limited to only around 1,000 observations once we restrict the size of our sample, and two control variables are now omitted due to being indistinguishable from the time-based fixed effects. The same lack of data is true for our analysis of any changes of ethnicity in an area.

On the other hand, our analysis of employment characteristics is much more robust in its volume of data, and generally contradicts the assertion that improved rail accessibility causes gentrification. As a proxy for increasing the proportion of professionals in an area, we use three employment categories: "Managers, Directors and Senior Officials"; "Professional Occupations"; and "Associate Professionals and Technical Occupations". Our results indicate no statistically significant change in any of them. On the other hand we select a range of categories as a proxy for working-class occupations. We see a reduction in "Machinery and Plant Operatives" but then no statistically significant change in "Elementary Occupations" or "Leisure and Care" workers. We also see an interesting statistically significant increase in "Sales and Customer Service" workers. This last point exemplifies another caveat in that we are limited by having to use proxies for gentrification. In this case, it isn't unreasonable to conclude that customer service is generally a lower paid occupation, while sales can be very lucrative with high salaries and commission. On the face of it, there is little commonality between these two categories, which makes it difficult to interpret whether an increase in the proportion of these employees provides evidence of gentrification or not. There is also now an interesting juxtaposition between changes in age and a lack of changes in employment.

There appears to be a statistically significant increase in younger workers, but no change in the structure of jobs. This suggests an unlikely conclusion where a younger population moves into an area with the same proportional breakdown of employment as existing residents. On the other hand, this balance could be explained by a reduction in the proportion of over-65s, which would in turn increase the proportion of younger residents without having a material impact on employment as they would not be working. Ultimately both of these mechanisms are somewhat speculative, which raises questions for the robustness of our results.

So what does this say for identifying gentrification? Ultimately our analysis aligns with existing findings. There appears to be a fairly consistent narrative on house price appreciation, but other indicators of gentrification are either inconclusive or contradictory to what we would expect to observe. It is clear that assessing the marginal impacts of improved rail accessibility is a useful avenue for analysis, yet future research should attempt to correct for the weaknesses identified in our methodology. From a methodological point of view, this could be done by focusing on better identifying causal effects, such as the use of instrumental variables. On the other hand, many of the issues are related to the availability of data. As mentioned previously, gentrification is a slow process. While we looked over a period of three years, future research could examine these changes over a longer period of time to better capture if and how improved rail accessibility fits into the process of gentrification.

6 Conclusions

Gentrification is the process by which capital and people flow into an area at the expense of the previous residents. Among other consequences, this broadly results in house price appreciation, and displacement of working class, older residents and those from ethnic minorities with young, white professionals. This paper has studied whether improving rail accessibility has a measurable impact on the process of gentrification. Existing literature has assessed whether new stations act as a catalyst for this process, however our analysis takes a new approach of measuring whether indicators of gentrification respond to marginal changes in rail accessibility, measured through changes in Generalised Journey Time. While we do find a small appreciation in house prices in response to improved accessibility, the demographic indicators do not present a coherent story. While the age profile of the residents around a station does appear to get younger, their employment profile doesn't change. Alongside some weaknesses in the volume of data, it is difficult to conclude that an increase in the proportion of young white professionals occurs as a result of improved Rail Accessibility. Ultimately our analysis aligns with the existing literature, finding that there is no conclusive evidence of gentrification resulting from changes in Rail Accessibility.

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Appendix A1: Summary Statistics

Variable/Year	Mean	p25	Median	p75	SD
1999					
GJT	83.24	41.3	62.10	100.5	66.16
Journey Time	47.86	16.8	31.00	59.2	49.12
Weighted GJT	32980.39	2995.82	6997.45	28121.77	66351.11
Distance (km)	34.71	8.6	17.40	40	47.11
Journeys	45265.07	4860	10401.00	28302	158914.22
2003					
GJT	82	40.6	60.90	98.2	65.72
Journey Time	47.7	16.8	30.80	58.8	49.24
Weighted GJT	32757.67	2962.69	6852.91	27431.36	66226.86
Distance (km)	34.71	8.6	17.40	40	47.11
Journeys	50866.6	5849	11864.00	32365	168580.55
2007					
GJT	80.5	40.3	60.40	97.2	63.39
Journey Time	47.44	17	31.10	58.8	47.98
Weighted GJT	32282.97	2937.2	6777.27	26974.12	65070.76
Distance (km)	34.71	8.6	17.40	40	47.11
Journeys	61995.19	7653	15121.00	40850	204175.16
2011					
GJT	78.95	39.9	59.50	95.5	61.92
Journey Time	46.88	17	31.10	58.3	46.96
Weighted GJT	31455.74	2866.89	6703.47	26523.14	62897.78
Distance (km)	34.71	8.6	17.40	40	47.11
Journeys	68490.36	9597	18608.00	48790	205458.27
2015					
GJT	78.05	39.4	59.00	94.05	61.14
Journey Time	46.55	17	31.10	57.7	46.57
Weighted GJT	31143.03	2840.96	6607.97	26039.33	62296.11
Distance (km)	34.71	8.6	17.40	40	47.11
Journeys	75400.23	10965	21368.00	54789	199350.19

Table 1: Summary Statistics for Transport Variables

Year	**Mean**	**p10**	**p25**	**Median**	**p75**	**p90**	**SD**
1995	65230.23	33160	42826.19	56220.93	76409.15	105246.15	37311.42
1996	65937.73	32900	42896.15	56646.97	77470.37	107323	38629.91
1997	70656.13	33825	44864.29	60125.8	83536.96	116759.3	43609.84
1998	78431.58	35094.86	47597.48	65563.4	93224.46	133308.53	52377.03
1999	85786.42	36416.67	50231.57	70944.47	103149.51	148801.13	59101.79
2000	98488.33	38353.54	54715.00	80643.19	120249.88	174769.39	71393.05
2001	111476.87	40822.13	60392.83	91764.29	137480.76	199218.95	82260.34
2002	126994.83	45915.38	69952.88	108056.35	158389.34	223581.03	89168.92
2003	150261.68	57490.91	87404.62	132772.79	187635.8	255972.92	95924.02
2004	171272.98	74896.3	108175.00	153481.48	208866.07	280232.69	99690.37
2005	186971.63	90037.44	122836.17	167145.79	223801.72	298460	103312.66
2006	195831.2	98175.47	129018.60	173300	232127.07	311882.35	109473.14
2007	212756.29	105812.28	137238.91	185204.7	250178.75	341655.43	125837.28
2008	222329.73	107468.18	139182.90	189556.25	259951.39	359559.38	145511.59
2009	206508.31	98285.71	128416.67	174448.25	240468.37	336400	140773.38
2010	212835.94	96813.16	129476.67	178666.11	250071.43	351205	147405.68
2011	217892.73	94535.19	128136.22	180000	255907.03	367173.91	161773.58
2012	218897.77	93000	126891.67	179535.42	256096.15	369107.55	175630.43
2013	225968.69	93519.23	127847.83	182500	263606.79	381600	194303.51
2014	240469.89	96652.94	132675.00	191122.49	279804.17	411402.14	214064.87
2015	259063.2	100550	139340.74	204758.26	306083.33	451555	229218.01
2016	276513.76	104828.93	145761.67	219022.22	333125	489544.04	236563.68
2017	291671.06	110083.33	152946.42	232452.95	353570.2	516031.25	251192.9
2018	299997.96	114400	159704.84	242501.88	364651.32	525187.44	251866.84
2019	302910.24	118765	164941.94	246900	366645.83	524205	258617.54

Table 2: Summary Statistics for House Prices

Variable/Year	Mean	p25	Median	p75	SD
2002					
age 0 14 prop 1km	18.3	16.64	18.34	20.02	2.98
age 15 29 prop 1km	18.53	14.88	17.44	20.42	6.11
age 30 44 prop 1km	22.53	20.6	22.35	24.28	3.19
age 45 64 prop 1km	23.94	21.17	24.05	26.77	4.29
age 65plus prop 1km	16.71	13.5	16.28	19.33	4.94
2012					
age 0 14 prop 1km	17.09	15.51	17.07	18.65	3.03
age 15 29 prop 1km	19.42	15	18.06	21.56	7.31
age 30 44 prop 1km	20.58	18	20.11	22.62	4.05
age 45 64 prop 1km	25.73	23.2	26.19	28.73	4.65
age 65plus prop 1km	17.18	13.14	17.05	20.75	5.95

Table 3: Summary Statistics for Local Age Composition

Year/Variable					
2004	Mean	p25	Median	p75	SD
Senior Officials	.46	0	0.02	.18	1.8
Professionals	.56	0	0.00	.17	2.43
Associate Professionals	12.27	3.77	7.84	16.62	12.24
Leisure and Carework	5.52	2.08	3.80	6.72	6.25
Sales and Customer Service	16.86	9	14.07	21.93	11.1
Machinery Operatives	26.08	16.1	24.04	33.48	13.97
Elementary Occupations	5.8	3.36	4.85	6.85	4.28
2008					
Senior Officials	.47	.02	0.10	.36	1.29
Professionals	.5	0	0.00	.14	2.13
Associate Professionals	10.34	2.96	6.45	13.48	10.89
Leisure and Carework	5.28	2.01	3.61	6.25	6.12
Sales and Customer Service	18.49	10.28	16.19	24.17	11.28
Machinery Operatives	27.36	17.16	25.20	35.11	14.13
Elementary Occupations	5.86	3.44	4.95	7.18	4.08
2012					
Senior Officials	.19	0	0.00	.05	1.01
Professionals	1.21	.03	0.23	1	3.18
Associate Professionals	8.58	1.86	4.84	11.33	10.04
Leisure and Carework	7.49	3.49	5.81	9.33	6.41
Sales and Customer Service	22.05	13.06	20.03	28.66	12.19
Machinery Operatives	28.66	18.41	26.73	37.1	14.25
Elementary Occupations	5.17	2.96	4.34	6.18	3.69
2016					
Senior Officials	.26	0	0.00	.09	1.29
Professionals	1.14	.03	0.25	.95	2.76
Associate Professionals	8.03	1.68	4.34	10.34	9.63
Leisure and Carework	7.86	3.86	6.11	9.88	6.64
Sales and Customer Service	18.47	10.84	16.33	24.02	10.77
Machinery Operatives	27.83	17.7	26.06	35.94	13.99
Elementary Occupations	5.11	2.84	4.32	6.23	3.93

Table 4: Summary Statistics for Local Employment Composition

Year/Variable					
2002	Mean	p25	Median	p75	SD
White British	.92	.92	0.97	.99	.11
Indian	.02	0	0.00	.02	.03
Pakistani	.01	0	0.00	.01	.02
Bangladeshi	0	0	0.00	0	.02
Chinese	0	0	0.00	.01	0
Other Asian	0	0	0.00	0	.01
Black African	.01	0	0.00	0	.03
Black Caribbean	.01	0	0.00	.01	.02
Black Other	0	0	0.00	0	0
Other/Mixed Ethnicities	.02	.01	0.01	.02	.02
2012					
White British	.89	.86	0.95	.98	.14
Indian	.02	0	0.01	.02	.03
Pakistani	.02	0	0.00	.01	.03
Bangladeshi	.01	0	0.00	0	.02
Chinese	.01	0	0.00	.01	.01
Other Asian	.01	0	0.01	.01	.02
Black African	.02	0	0.00	.02	.03
Black Caribbean	.01	0	0.00	0	.02
Black Other	0	0	0.00	0	.01
Other/Mixed Ethnicities	.03	.01	0.02	.03	.03

Table 5: Summary Statistics for District Level Ethnic Composition

Appendix A2: Figures

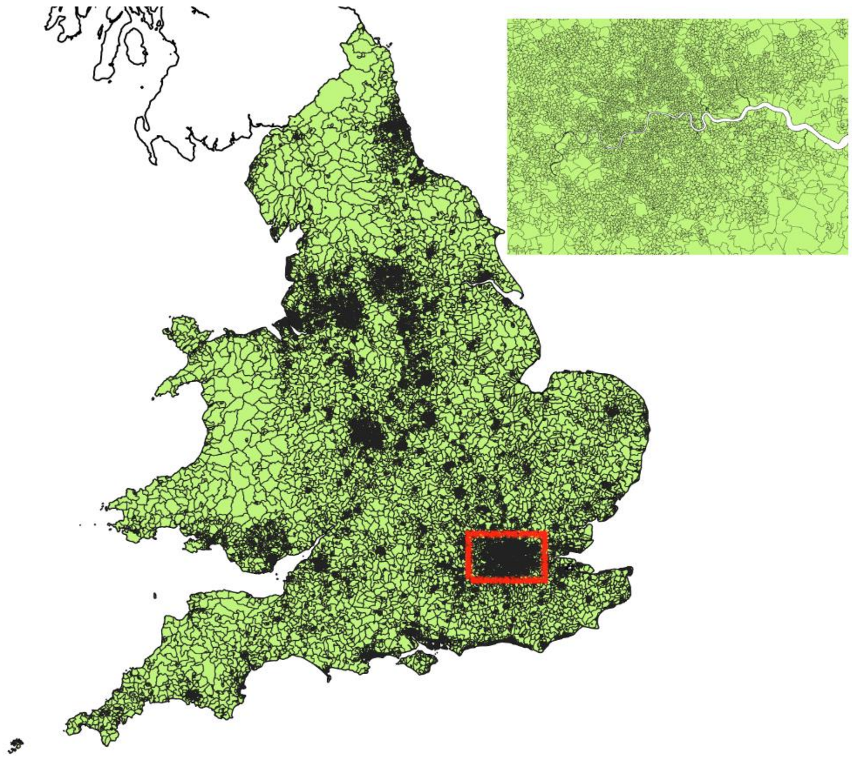

Figure 1: LSOA Map of England and Wales

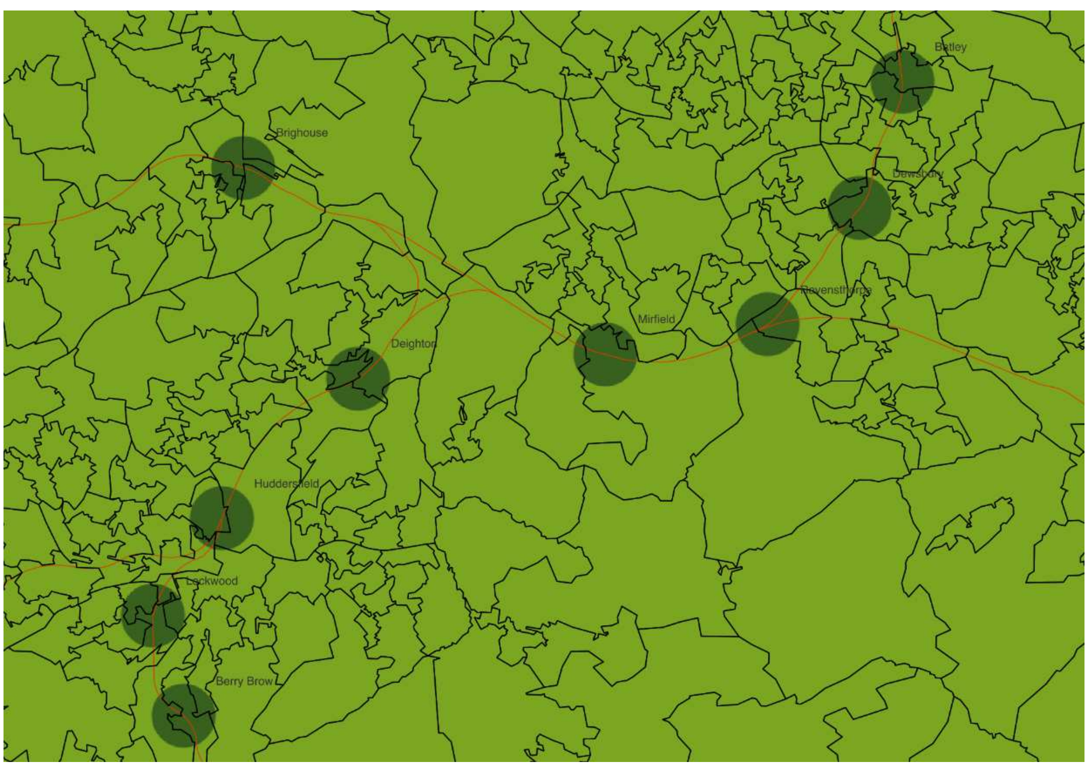

Figure 2: Intersection of 1km station boundaries and LSOAs

Appendix A3: Results Tables

A3.1: Pooled OLS

	HP	Age 0-14	Age 15-29	Age 30-44	Age 45-64	Age 65+	% White British
RA	-0.01***	-.013	-.232***	-.327***	.316***	.256***	.012***
	(.001)	(.016)	(.047)	(.017)	(.018)	(.019)	(.001)
Disposable Income	0***	0***	-.002***	0***	.001***	0***	0***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
GVA	0	0***	.001***	0	0***	0***	0***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Average Delay	-.011	2.437***	-7.661***	-1.709***	3.57***	3.363***	.07***
	(0.013)	(.137)	(.415)	(.177)	(.157)	(.171)	(.004)
Car Ownership	.004***	.042***	.16***	.111***	-.132***	-.182***	-.011***
	(0)	(.006)	(.016)	(.007)	(.006)	(.006)	(0)
Observations	847344	63844	63844	63844	63844	63844	63844
R-squared	.476	.141	.272	.406	.243	.225	.53

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 6: Pooled OLS Results for House Prices, Age and Ethnicity composition

	Senior Officials	Professionals	Associate Professionals	Leisure & Carework	Sales & Customer Service	Plant Operatives	Elementary Occupations
RA	.008***	.021***	.243***	.043*	-.652***	.144***	-.02***
	(.001)	(.004)	(.016)	(.024)	(.032)	(.034)	(.007)
Disposable Income	0***	0***	0***	0***	-.001***	0***	0***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
GVA	0***	0*	0***	0	0***	0***	0***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Average Delay	.037***	-.097***	2.512***	-.93***	-4.615***	-.567*	.231***
	(.005)	(.037)	(.109)	(.298)	(.313)	(.326)	(.074)
Car Ownership	-.002***	-.017***	-.067***	-.027**	.073***	.077***	.046***
	(0)	(.002)	(.005)	(.011)	(.015)	(.014)	(.003)
Observations	766030	766030	766030	766030	766030	766030	766030
R-squared	.005	.011	.037	.027	.093	.049	.079

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 7: Pooled OLS Results for Employment composition

A3.2: Fixed Effects

	(1) HP	(2) HP Q1	(3) HP Q2	(4) HP Q3	(5) HP Q4	(6) HP Q5	(7) HP Q6
RA	-.0004***	-.0005***	-.0005***	-.0005***	.0004***	.0004***	.0004***
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Disposable Income	0***	0***	0***	0***	0***	0***	0***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
GVA	0***	0***	0***	0***	0***	0***	0***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Average Delay	-.0018**	-.0019***	-.0019***	-.0019***	-.0017**	-.0017**	-.0018**
	(.0007)	(.0007)	(.0007)	(.0007)	(.0007)	(.0007)	(.0007)
Car Ownership	.0022***	.0022***	.0022***	.0022***	.0022***	.0022***	.0022***
	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)
Observations	2057288	2053997	2053923	2053891	2053938	2053126	2052339
R-squared	.9444	.9445	.9445	.9445	.9445	.9444	.9444

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 8: Fixed Effects Regression for House Prices lagged up to 6 quarters after timetable change

	(1) HP Q7	(2) HP Q8	(3) HP Q9	(4) HP Q10	(5) HP Q11	(6) HP Q12
RA	-.0004***	-.0004***	-.0005***	-.0005***	-.0005***	-.0005***
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Disposable Income	0***	0***	0***	0***	0***	0***
	(0)	(0)	(0)	(0)	(0)	(0)
GVA	0***	0***	0***	0***	0***	0***
	(0)	(0)	(0)	(0)	(0)	(0)
Average Delay	-.0018**	-.0018***	-.0019***	-.0019***	-.002***	-.002***
	(.0007)	(.0007)	(.0007)	(.0007)	(.0007)	(.0007)
Car Ownership	.0022***	.0022***	.0022***	.0022***	.0022***	.0022***
	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)
Observations	2051619	2050821	2049538	2048096	2046684	2045308
R-squared	.9444	.9444	.9444	.9443	.9443	.9443

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 9: Fixed Effects Regression for House Prices lagged from 7 to 12 quarters after timetable change

	(1) Senior Officials Y0	(2) Senior Officials Y1	(3) Senior Officials Y2	(4) Senior Officials Y3
RA	.0008***	.0009***	.0008***	.0008***
	(.0003)	(.0003)	(.0003)	(.0003)
Disposable Income	0***	0***	0***	0***
	(0)	(0)	(0)	(0)
GVA	0***	0***	0***	0***
	(0)	(0)	(0)	(0)
Average Delay	.0002	.0002	.0001	0
	(.0013)	(.0013)	(.0013)	(.0013)
Car Ownership	-.0037**	-.0037**	-.0037**	-.0037**
	(.0017)	(.0017)	(.0017)	(.0017)
Observations	1836304	1833279	1830041	1825269
R-squared	.3306	.3305	.3305	.3305

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 10: Fixed Effects Regression for Managers, Directors and Senior Officials lagged from 0 to 3 years after timetable change

	(1) Professionals Y0	(2) Professionals Y1	(3) Professionals Y2	(4) Professionals Y3
RA	.0005	.0004	.0007	.0012
	(.0012)	(.0012)	(.0012)	(.0012)
Disposable Income	0***	0***	0***	0***
	(0)	(0)	(0)	(0)
GVA	0***	0***	0***	0***
	(0)	(0)	(0)	(0)
Average Delay	-.0254**	-.0255**	-.0241**	-.0235**
	(.0111)	(.0111)	(.0111)	(.0111)
Car Ownership	.0064	.0064	.0065	.0065
	(.0164)	(.0164)	(.0164)	(.0164)
Observations	1836304	1833279	1830041	1825269
R-squared	.6343	.6343	.6343	.6343

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 11: Fixed Effects Regression for Professional Occupations lagged from 0 to 3 years after timetable change

	(1) Associates Y0	(2) Associates Y1	(3) Associates Y2	(4) Associates Y3
RA	.0076**	.0102**	.0098***	.009**
	(.0035)	(.0035)	(.0036)	(.0036)
Disposable Income	.0001***	.0001***	.0001***	.0001***
	(0)	(0)	(0)	(0)
GVA	-.0001***	-.0001***	-.0001***	-.0001***
	(0)	(0)	(0)	(0)
Average Delay	.0527**	.055***	.0563***	.0554***
	(.0206)	(.0206)	(.0205)	(.0206)
Car Ownership	-.0239	-.0237	-.0238	-.0238
	(.0387)	(.0387)	(.0387)	(.0388)
Observations	1836304	1833279	1830041	1825269
R-squared	.8646	.8646	.8645	.8643

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 12: Fixed Effects Regression for Associate Professionals and Technical Occupations lagged from 0 to 3 years after timetable change

	(1) Care and Leisure Y0	(2) Care and Leisure Y1	(3) Care and Leisure Y2	(4) Care and Leisure Y3
RA	.0018	.0007	-.0004	-.0014
	(.0036)	(.0036)	(.0036)	(.0036)
Disposable Income	-.0004***	-.0004***	-.0004***	-.0003***
	(0)	(0)	(0)	(0)
GVA	.0002***	.0002***	.0002***	.0002***
	(0)	(0)	(0)	(0)
Average Delay	.0898***	.089***	.0774***	.0702***
	(.0272)	(.0272)	(.0269)	(.0269)
Car Ownership	.0476	.0475	.0471	.049
	(.0454)	(.0454)	(.0452)	(.0446)
Observations	1836304	1833279	1830041	1825269
R-squared	.7291	.7293	.7288	.7259

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 13: Fixed Effects Regression for Leisure, Care and Other Services lagged from 0 to 3 years after timetable change

	(1) Sales and Customer Service Y0	(2) Sales and Customer Service Y1	(3) Sales and Customer Service Y2	(4) Sales and Customer Service Y3
RA	-.0373***	-.0377***	-.0386***	-.0396***
	(.0069)	(.0069)	(.0069)	(.0069)
Disposable Income	.0002***	.0002***	.0002***	.0001***
	(0)	(0)	(0)	(0)
GVA	-.0001***	-.0001***	-.0001***	-.0001**
	(0)	(0)	(0)	(0)
Average Delay	-.3128***	-.3108***	-.3162***	-.302***
	(.0575)	(.0577)	(.0568)	(.0569)
Car Ownership	-.0102	-.0103	-.0104	-.0116
	(.0433)	(.0432)	(.0434)	(.0424)
Observations	1836304	1833279	1830041	1825269
R-squared	.801	.8012	.8014	.8017

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 14: Fixed Effects Regression for Sales and Customer Service lagged from 0 to 3 years after timetable change

	(1) Plant and Machinery Y0	(2) Plant and Machinery Y1	(3) Plant and Machinery Y2	(4) Plant and Machinery Y3
RA	.0689***	.07***	.0713***	.0716***
	(.0068)	(.0069)	(.0069)	(.0069)
Disposable Income	-.0001***	-.0001***	-.0001***	-.0002***
	(0)	(0)	(0)	(0)
GVA	0	0	0	0
	(0)	(0)	(0)	(0)
Average Delay	-.0095	-.0109	-.0094	.0037
	(.048)	(.0482)	(.0477)	(.047)
Car Ownership	.0766	.0767	.0771	.0762
	(.116)	(.116)	(.1161)	(.1165)
Observations	1836304	1833279	1830041	1825269
R-squared	.8703	.8704	.8703	.8702

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 15: Fixed Effects Regression for Plant and Machinery Operatives lagged from 0 to 3 years after timetable change

	(1) Elementary Occupations Y0	(2) Elementary Occupations Y1	(3) Elementary Occupations Y2	(4) Elementary Occupations Y3
RA	-.0026	-.0018	-.0035*	-.0035*
	(.0018)	(.0018)	(.0018)	(.0018)
Disposable Income	0	0	0	0***
	(0)	(0)	(0)	(0)
GVA	0***	0***	0***	0***
	(0)	(0)	(0)	(0)
Average Delay	.0179	.0202*	.0174	.0168
	(.0114)	(.0114)	(.0114)	(.0114)
Car Ownership	.025	.025	.0249	.0243
	(.0298)	(.0298)	(.0298)	(.0299)
Observations	1836304	1833279	1830041	1825269
R-squared	.6883	.688	.6878	.6877

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 16: Fixed Effects Regression for Elementary Occupations lagged from 0 to 3 years after timetable change

	(1) Age 0-14 Y0	(2) Age 0-14 Y1	(3) Age 0-14 Y2	(4) Age 0-14 Y3
RA	.0084***	.0083***	.0071***	.0075***
	(.0024)	(.0024)	(.0023)	(.0024)
Disposable Income	-.0003***	-.0003***	-.0003***	-.0004***
	(0)	(0)	(0)	(0)
GVA	0***	0***	0***	0***
	(0)	(0)	(0)	(0)
Average Delay	.0107	.0109	.0115	.0094
	(.0108)	(.0107)	(.0107)	(.0111)
nts_households0~r	.0339**	.0339**	.0335**	.032**
	(.0148)	(.0148)	(.015)	(.0153)
Observations	151083	150809	149954	146274
R-squared	.9837	.9838	.984	.9842

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 17: Fixed Effects Regression for Proportion of Population Aged 0-14 lagged from 0 to 3 years after timetable change

	(1) Age 15-29 Y0	(2) Age 15-29 Y0	(3) Age 15-29 Y0	(4) Age 15-29 Y0
RA	-.0029	-.0032	-.0016	-.0025
	(.0054)	(.0054)	(.0054)	(.0055)
Disposable Income	0	0	.0001	0
	(.0001)	(.0001)	(.0001)	(.0001)
GVA	0	0	0	0
	(0)	(0)	(0)	(0)
Average Delay	.0144	.0137	.014	.0122
	(.0182)	(.018)	(.0179)	(.0189)
Car Ownership	.0214	.0214	.0223	.0195
	(.0188)	(.0188)	(.019)	(.0185)
Observations	151083	150809	149954	146274
R-squared	.9905	.9906	.9907	.9907

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 18: Fixed Effects Regression for Proportion of Population Aged 15-29 lagged from 0 to 3 years after timetable change

	(1) Age 30-44 Y0	(2) Age 30-44 Y1	(3) Age 30-44 Y2	(4) Age 30-44 Y3
RA	-.0263***	-.0263***	-.0251***	-.0258***
	(.0032)	(.0032)	(.0032)	(.0033)
Disposable Income	.0002***	.0002***	.0002***	.0002***
	(.0001)	(.0001)	(.0001)	(.0001)
GVA	0	0	0	0
	(0)	(0)	(0)	(0)
Average Delay	-.0323***	-.032***	-.0303***	-.0264**
	(.0117)	(.0116)	(.0115)	(.012)
Car Ownership	.1234***	.1234***	.1234***	.1224***
	(.0267)	(.0267)	(.0267)	(.0267)
Observations	151083	150809	149954	146274
R-squared	.9873	.9874	.9874	.9869

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 19: Fixed Effects Regression for Proportion of Population Aged 30-44 lagged from 0 to 3 years after timetable change

	(1) Age 45-64 Y0	(2) Age 45-64 Y1	(3) Age 45-64 Y2	(4) Age 45-64 Y3
RA	.0113***	.0114***	.0107***	.0116***
	(.0028)	(.0028)	(.0028)	(.0029)
Disposable Income	-.0001	-.0001	-.0001	0
	(.0001)	(.0001)	(.0001)	(.0001)
GVA	0	0	0	0
	(0)	(0)	(0)	(0)
Average Delay	-.014	-.0138	-.0138	-.0121
	(.0127)	(.0127)	(.0127)	(.0132)
Car Ownership	-.0588**	-.0588**	-.059**	-.0567**
	(.0267)	(.0267)	(.0268)	(.0262)
Observations	151083	150809	149954	146274
R-squared	.9871	.9872	.9872	.9872

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 20: Fixed Effects Regression for Proportion of Population Aged 45-64 lagged from 0 to 3 years after timetable change

	(1) Age 65+ Y0	(2) Age 65+ Y1	(3) Age 65+ Y2	(4) Age 65+ Y3
RA	.0095***	.0097***	.0089***	.0092***
	(.0028)	(.0028)	(.0028)	(.0029)
Disposable Income	.0001*	.0001*	.0001*	.0001**
	(.0001)	(.0001)	(.0001)	(.0001)
GVA	0	0	0	0**
	(0)	(0)	(0)	(0)
Average Delay	.0211*	.0212*	.0187	.0169
	(.0116)	(.0116)	(.0116)	(.0121)
nts_households0~r	-.12***	-.12***	-.1201***	-.1171***
	(.0352)	(.0352)	(.0352)	(.0353)
Observations	151083	150809	149954	146274
R-squared	.9907	.9908	.9908	.9907

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 21: Fixed Effects Regression for Proportion of Population Aged 65+ lagged from 0 to 3 years after timetable change

	(1) % White British Y0	(2) % White British Y1	(3) % White British Y2	(4) % White British Y3
RA	0	0	0	0
	(0)	(0)	(0)	(0)
Disposable Income	0***	0***	0***	0***
	(0)	(0)	(0)	(0)
GVA	0***	0***	0***	0***
	(0)	(0)	(0)	(0)
Average Delay	-.0001	-.0001	-.0001	-.0001
	(.0001)	(.0001)	(.0001)	(.0001)
Car Ownership	-.0045***	-.0045***	-.0046***	-.0044***
	(.0015)	(.0015)	(.0015)	(.0016)
Observations	151083	150809	149954	146274
R-squared	.9989	.9989	.9989	.9989

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 22: Fixed Effects Regression for Proportion of Population Identifying as White British lagged from 0 to 3 years after timetable change

A3.3: Adjusted Sample Fixed Effects

	(1) HP Q0	(2) HP Q1	(3) HP Q2	(4) HP Q3	(5) HP Q4	(6) HP Q5	(7) HP Q6
RA	-.0002	-.0077***	-.0118***	-.0084***	-.0002	-.0002	-.0001
	(.0002)	(.0011)	(.0015)	(.0012)	(.0003)	(.0003)	(.0003)
Disposable Income	-.0002**	-.0002**	-.0002**	-.0002**	-.0002**	-.0002**	-.0002**
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
GVA	.0001**	.0001**	.0001**	.0001**	.0001**	.0001**	.0001**
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Average Delay	-.0077	-.0425***	-.0611***	-.0454***	-.007	-.0071	-.0067
	(.0058)	(.0078)	(.0091)	(.0082)	(.0058)	(.0058)	(.0059)
Car Ownership	.1274**	.1242**	.1222**	.1228**	.1279**	.1275**	.1278**
	(.0564)	(.0564)	(.0565)	(.0564)	(.0564)	(.0564)	(.0564)
Observations	11740	11654	11647	11645	11650	11574	11512
R-squared	.9745	.9747	.9747	.9747	.9747	.9744	.9748

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 23: Fixed Effects Regression for House Prices lagged from 0 to 6 quarters after timetable change

	(1) Senior Officials Y0	(2) Senior Officials Y1	(3) Senior Officials Y2	(4) Senior Officials Y3
RA	-.0008*	-.0008	-.0008*	-.0008*
	(.0004)	(.0005)	(.0005)	(.0005)
Disposable Income	0***	0***	0***	0***
	(0)	(0)	(0)	(0)
GVA	0***	0***	0***	0***
	(0)	(0)	(0)	(0)
Average Delay	-.0039*	-.0039*	-.004*	-.004*
	(.0021)	(.0022)	(.0022)	(.0023)
Observations	8840	8751	8462	8439
R-squared	.9973	.9973	.9973	.9973

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 24: Fixed Effects Regression for Managers, Directors and Senior Officials lagged from 0 to 3 years after timetable change

	(1) Professionals Y0	(2) Professionals Y1	(3) Professionals Y2	(4) Professionals Y3
RA	-.0009	-.0021	-.0022	-.0021
	(.0012)	(.0017)	(.0017)	(.0017)
Disposable Income	.0001***	.0001***	.0001***	.0001***
	(0)	(0)	(0)	(0)
GVA	-.0001***	-.0001***	-.0001***	-.0001***
	(0)	(0)	(0)	(0)
Average Delay	-.0042	-.0098	-.0098	-.0097
	(.0054)	(.0077)	(.0077)	(.0077)
Observations	8840	8751	8462	8439
R-squared	.9886	.9886	.9884	.9884

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 25: Fixed Effects Regression for Professional Occupations lagged from 0 to 3 years after timetable change

	(1) Associates Y0	(2) Associates Y1	(3) Associates Y2	(4) Associates Y3
RA	.0157	.0123	.0118	.0125
	(.0263)	(.0335)	(.0335)	(.0334)
Disposable Income	-.0004***	-.0004***	-.0004***	-.0004***
	(0)	(0)	(0)	(0)
GVA	.0002***	.0002***	.0002***	.0002***
	(0)	(0)	(0)	(0)
Average Delay	.0661	.0493	.0468	.05
	(.1218)	(.1525)	(.1526)	(.1518)
Observations	8840	8751	8462	8439
R-squared	.9776	.9775	.9769	.9769

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 26: Fixed Effects Regression for Associate Professional and Technical Occupations lagged from 0 to 3 years after timetable change

	(1) Care and Leisure Y0	(2) Care and Leisure Y1	(3) Care and Leisure Y2	(4) Care and Leisure Y3
RA	-.0821*	-.0706	-.0714	-.0724
	(.0426)	(.0473)	(.0474)	(.0476)
Disposable Income	-.0012***	-.0012***	-.0012***	-.0012***
	(0)	(0)	(0)	(0)
GVA	.0002***	.0002***	.0002***	.0002***
	(0)	(0)	(0)	(0)
Average Delay	-.3818*	-.3227	-.3262	-.331
	(.1974)	(.2153)	(.2158)	(.2165)
Observations	8840	8751	8462	8439
R-squared	.9933	.9933	.9919	.9919

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 27: Fixed Effects Regression for Leisure, Care and Other Services lagged from 0 to 3 years after timetable change

	(1) Sales and Customer Service Y0	(2) Sales and Customer Service Y1	(3) Sales and Customer Service Y2	(4) Sales and Customer Service Y3
RA	-.5933***	-.6065**	-.6079**	-.6122**
	(.229)	(.2453)	(.2461)	(.2476)
Disposable Income	-.0001***	-.0001***	-.0001***	-.0001***
	(0)	(0)	(0)	(0)
GVA	.0002***	.0002***	.0002***	.0002***
	(0)	(0)	(0)	(0)
Average Delay	-2.7333**	-2.7433**	-2.7494**	-2.7692**
	(1.0612)	(1.1161)	(1.1197)	(1.1268)
Observations	8840	8751	8462	8439
R-squared	.9893	.9892	.9891	.9891

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 28: Fixed Effects Regression for Sales and Customer Services lagged from 0 to 3 years after timetable change

	(1) Plant and Machinery Y0	(2) Plant and Machinery Y1	(3) Plant and Machinery Y2	(4) Plant and Machinery Y3
RA	.7985**	.8294**	.8323**	.8383**
	(.3481)	(.3732)	(.3745)	(.3769)
Disposable Income	.0017***	.0017***	.0017***	.0017***
	(0)	(0)	(0)	(0)
GVA	-.0007***	-.0007***	-.0007***	-.0007***
	(0)	(0)	(0)	(0)
Average Delay	3.6842**	3.7575**	3.77**	3.7979**
	(1.6131)	(1.6978)	(1.7034)	(1.7145)
Observations	8840	8751	8462	8439
R-squared	.9715	.9712	.9705	.9705

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 29: Fixed Effects Regression for Plant and Machinery Operatives lagged from 0 to 3 years after timetable change

	(1) Elementary Occupations Y0	(2) Elementary Occupations Y0	(3) Elementary Occupations Y0	(4) Elementary Occupations Y0
RA	-.0091	-.0159	-.0154	-.0148
	(.0097)	(.0114)	(.0113)	(.0112)
Disposable Income	.0005***	.0005***	.0005***	.0005***
	(0)	(0)	(0)	(0)
GVA	-.0002***	-.0002***	-.0002***	-.0002***
	(0)	(0)	(0)	(0)
Average Delay	-.0336	-.0634	-.0612	-.0587
	(.0462)	(.0534)	(.0532)	(.0524)
Observations	8840	8751	8462	8439
R-squared	.9818	.9817	.981	.9809

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 30: Fixed Effects Regression for Elementary Occupations lagged from 0 to 3 years after timetable change

	(1) Age 0-14 Y0	(2) Age 0-14 Y1	(3) Age 0-14 Y2	(4) Age 0-14 Y3
RA	.437***	.4678***	.4683***	.4691***
	(.1567)	(.1676)	(.1679)	(.1676)
Average Delay	62.5866***	54.1322***	54.1835***	54.2823***
	(22.4497)	(19.3952)	(19.4258)	(19.3947)
Observations	1021	1010	800	781
R-squared	.9732	.9731	.9702	.9697

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 31: Fixed Effects Regression for Proportion of Population Aged 0-14 lagged from 0 to 3 years after timetable change

	(1) Age 15-29 Y0	(2) Age 15-29 Y1	(3) Age 15-29 Y2	(4) Age 15-29 Y3
RA	-.6269***	-.6712***	-.6718***	-.6731***
	(.2249)	(.2405)	(.2409)	(.2405)
Average Delay	-89.7967***	-77.6668***	-77.7403***	-77.8821***
	(32.2099)	(27.8275)	(27.8713)	(27.8268)
Observations	1021	1010	800	781
R-squared	.9874	.9874	.9873	.9873

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 32: Fixed Effects Regression for Proportion of Population Aged 15-29 lagged from 0 to 3 years after timetable change

	(1) Age 30-44 Y0	(2) Age 30-44 Y1	(3) Age 30-44 Y2	(4) Age 30-44 Y3
RA	-.5483***	-.5871***	-.5876***	-.5887***
	(.1967)	(.2103)	(.2107)	(.2103)
Average Delay	-78.5385***	-67.9294***	-67.9937***	-68.1177***
	(28.1716)	(24.3387)	(24.377)	(24.338)
Observations	1021	1010	800	781
R-squared	.9863	.9861	.9721	.9692

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 33: Fixed Effects Regression for Proportion of Population Aged 30-44 lagged from 0 to 3 years after timetable change

	(1) Age 45-64 Y0	(2) Age 45-64 Y0	(3) Age 45-64 Y0	(4) Age 45-64 Y0
RA	.3631***	.3887***	.3891***	.3898***
	(.1302)	(.1393)	(.1395)	(.1393)
Average Delay	52.0028***	44.9781***	45.0207***	45.1028***
	(18.6533)	(16.1154)	(16.1407)	(16.1149)
Observations	1021	1010	800	781
R-squared	.987	.9869	.9848	.9843

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 34: Fixed Effects Regression for Proportion of Population Aged 45-64 lagged from 0 to 3 years after timetable change

	(1) Age 65+ Y0	(2) Age 65+ Y1	(3) Age 65+ Y2	(4) Age 65+ Y3
RA	.3752***	.4017***	.4021***	.4028***
	(.1346)	(.1439)	(.1442)	(.1439)
Average Delay	53.7454***	46.4854***	46.5294***	46.6143***
	(19.2784)	(16.6554)	(16.6816)	(16.655)
Observations	1021	1010	800	781
R-squared	.984	.9839	.9789	.9782

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 35: Fixed Effects Regression for Proportion of Population Aged 65+ lagged from 0 to 3 years after timetable change