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All hail? The impact of ride hailing platforms on the use of other transport modes

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Abstract

Does ride hailing complement or substitute other forms of transport, such as public transport? I employ Scottish Household Survey travel diary data from 16,712 individuals between 2012 and 2019 in a difference-in-differences examination of how ride hailing affected the use of other transport modes. Results reveal a small complementary effect on the use of public transport relative to driving a car in Glasgow, although this is not reflected in Edinburgh. The Glasgow effect appears to be more pronounced among individuals who are younger, male, employed and with higher levels of household income.

Keywords: ride hailing, public transport, technological innovation, sharing economy, difference-in-differences, travel diary

JEL: R41, R40, H42, O33

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1. Introduction

The modern advent of ride hailing offers an alternative form of urban transportation and a novel approach to car ownership, and thus represents an interesting development in city transport. In this study, I examine the impact of ride hailing on other modes of transport in the cities of Glasgow and Edinburgh in Scotland.

In 2015, the Paris Climate Change Agreement established the target of limiting the global temperature rise to 1.5 degrees Celsius (Masson-Delmotte et al., 2018). Having been responsible for 34 per cent of all carbon dioxide emissions in the United Kingdom (UK) in 2022 (UK Department for Energy Security and Net Zero, 2023a), transport is an important sector where a reduction in emissions is required to meet this target. The United Nations (UN, 2021) has also identified sustainable transport as a key enabler of a range of Sustainable Development Goals. The key to whether ride hailing can be viewed as a positive development in the transition to sustainable transport lies in its impact on other transport modes.

1.1. What is ride hailing?

The term 'ride hailing' is used to describe an arrangement where an individual requests a specific trip and is matched via a mobile application with a driver willing to meet that demand with a private car (Tirachini, 2019). It is among a range of mobility services linked to an emerging sharing economy that is based on internet platforms and smartphone applications (Miramontes et al., 2017). Ride hailing is also linked to an emerging concept of 'transport as a service', characterised by an increasingly blurred line between private and public transport with emphasis on the use rather than ownership of vehicles (Crozet, 2020; Webb, 2019; Miramontes et al., 2017). In the case of ride hailing, companies sign up car owners as drivers such that neither the company nor the consumer owns the vehicle in use (Crozet, 2020).

Where available, ride hailing involves a mobile application (app) that empowers the consumer to request a trip whenever and wherever they want, with no need to find a local taxi phone number or hail on the street. The consumer can check the price of the trip in advance, and the payment itself is also handled through the app, removing the need to pay in cash. The app also facilitates checking the journey duration and route in advance, reducing the need to provide directions or worry about expensive detours, and the consumer can follow journey progress on the app in real time. Hall et al. (2018) noted that ride hailing added a reliable and affordable option to city transport that also served areas of cities that were neglected by other transport modes.

In addition to these benefits, it has been argued that ride hailing boasts the potential to match passengers and drivers more efficiently than the street hailing of traditional taxis and can leverage internet-based technology to adjust prices in real time to consolidate supply and demand (Tirachini, 2019). Dynamic pricing means that ride hailing can sometimes be cheaper than hailing a taxi, although this will not always be the case, particularly during periods of high demand. Cohen et al. (2016) estimated that UberX (a low-cost product of ride hailing platform Uber) cost 20-30 per cent less than traditional taxis, and created USD6.8 billion in consumer surplus in the US in 2015.

In a review of literature, Tirachini (2019) noted that other terms for ride hailing have included 'ride sourcing', 'app-based ride services', 'ride booking' and 'on-demand ride services', and that companies facilitating this with mobile application technology have been referred to as 'transportation network companies (TNCs)'. Examples of such companies include Uber, Lyft, Cabify, Ola, DiDi Chuxing and RideAustin. Uber, having launched in 2009, had established a presence in approximately 800 cities within less than a decade (Tirachini, 2019). Figure 1 presents Google search frequency data (Google Trends, 2022) to illustrate the rapid rise of Uber between 2012 and 2019, both at a global level and in Scotland.

Although the terms have sometimes been used interchangeably in the literature, the concept of ride hailing is distinct from 'ride sharing', which is a platform used for carpooling

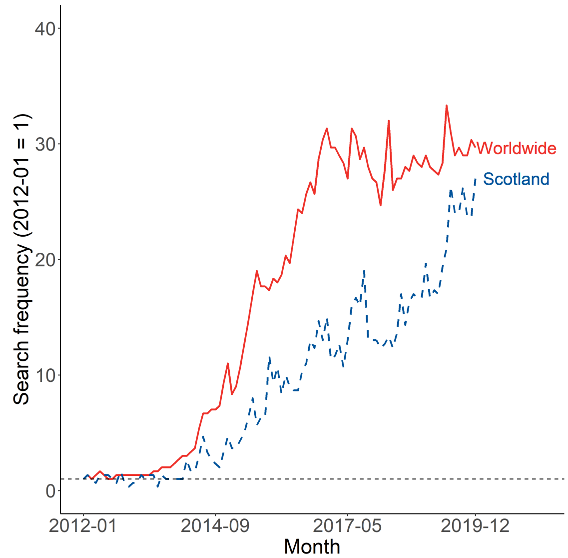


Figure 1: Frequency of Google searches for 'uber' search term, 2012-2019. Source: Author's analysis; Google Trends (2022).

rather than requesting a driver and private car, for example BlaBlaCar (Mitropoulos et al., 2021). TNCs often provide ride sharing in addition to ride hailing, for example Uber's UberPool, Lyft's LyftSharing or DiDi's Hitch. In a survey of ride hailing journeys in Denver, Colorado, Henao and Marshall (2018) found that the average vehicle occupancy was 1.4, indicating that ride hailing tended to be utilised as a driver and private car service rather than a car pooling arrangement. The present study will focus on ride hailing.

Overall, ride hailing platforms can be viewed as a new transport technology that has become available in cities. Studies of the effects of ride hailing follow a literature on the impact of transport innovation and development on cities, for example the effect of the private car on the socio-demographic geography of cities (LeRoy and Sonstelie, 1983) or the impact of interstate highways on suburbanisation (Baum-Snow, 2007).

1.2. Who uses ride hailing?

Ride hailing has been found to attract individuals seeking affordable, fast, point-to-point travel for journeys of between 10 and 30 minutes in duration (Tang et al., 2019). Many studies have examined the characteristics of ride hailing users, and factors in their decision to avail of ride hailing (Loa and Habib, 2021; Wang and Noland, 2021; Acheampong et al., 2020; Dias et al., 2019; Gehrke et al., 2019; Mitra et al., 2019; Sikder, 2019; Young and Farber, 2019; Henao and Marshall, 2018; Miramontes et al., 2017, for example). The literature review conducted by Tirachini (2019) found that ride hailing users tend to be younger, more highly educated and wealthier than the general population, although Gehrke et al. (2019) found a more balanced income distribution in a survey of ride hailing passengers in Boston, Massachusetts. In addition, in the US, Sikder (2019) presented evidence that African-Americans were less likely to use ride hailing, and that individuals working full-time with flexible hours were more likely than other workers or non-workers to utilise it.

Using US National Household Travel Survey 2017 data, Mitra et al. (2019) assessed the use of ride hailing among older adults. They found that those availing of ride hailing were more likely to be at the younger end of the age distribution, living alone, living in an urban area, more highly educated, wealthier and in possession of a smartphone (Mitra et al., 2019). Meanwhile, Wang and Noland (2021) employed data on ride hailing trips over the period of one month in Chengdu, China to show a positive association between ride hailing usage and several spatial factors, including population density, housing prices and subway proximity.

The Tirachini (2019) review found that reasons for choosing ride hailing as a transport mode include cost, travel time and comfort. Another factor Tirachini (2019) noted in the literature was avoiding the need for a designated driver, which was consistent with their finding that ride hailing appears to be used predominantly for occasional leisure trips rather than regular commuting, with the majority of users only turning to ride hailing a few times a month (Acheampong et al., 2020; Tirachini, 2019; Tirachini and del Río, 2019). The Denver survey by Henao and Marshall (2018) found that 94.5 per cent of passengers stated they were using ride hailing for the entire trip, rather than combining it with another transport mode. Peak demand times for ride hailing have been found to be Friday and Saturday nights in addition to typical 'rush hour' periods (Wang and Noland, 2021; Henao and Marshall, 2018).

1.3. How does ride hailing affect other forms of transport?

The indirect effect on other transport modes represents one of the main externalities of ride hailing. In relation to public transport, does ride hailing represent a complementary or a substitute good? Studies including Li et al. (2024), Tirachini (2019) and Hall et al. (2018) have highlighted this question as being crucial to whether ride hailing can be considered a sustainable alternative mode of transport. Stiglic et al. (2018) pointed to literature discussing the first- and last-mile problem in connecting a public transport network with trip origin and destination points, and contended that promoting the integration of ride hailing and public transport could potentially help to alleviate this. Equally, however, in a literature review on the effects of evolving urban transport systems, Webb (2019) noted that ride hailing could alternatively tempt individuals away from public transport in favour of a new, on-demand form of personalised transport.

The existence of substitution or complementary effects of ride hailing on public transport is an active debate in academic literature. The Tirachini (2019) literature review found mixed results on such effects. The review indicated that across multiple cities, studies have tended to find the substitution effect of ride hailing on public transport to be greater than the complementary effect, and that it has thus added to congestion (Tirachini, 2019).

Boisjoly et al. (2018) found the presence of ride hailing had no significant effect on the number of passenger trips on public transport between 2002 and 2015 in Canada and the US. However, drawing on aggregate agency-level data on public transport usage in the US, Hall et al. (2018) used variation in both the intensity and timing of Uber's entry across metropolitan areas in a difference-in-differences framework to reveal that ride hailing acted as a complement to public transport, with a 5 per cent increase in public transport use after 2 years. This effect was more pronounced for larger cities. Mitra et al. (2019) found that among older adults in the US, ride hailing users make more public transport trips than non-users, suggesting a possible complementarity between the two modes for this age group. Meanwhile, Shi et al. (2021b) found that the presence of ride hailing reduced the number of bus passengers but increased the number of rail passengers.

On the other hand, Acheampong et al. (2020) reported that ride hailing users in Ghana stated they would have used traditional taxis, public transport or private cars to complete the reference trip in the absence of ride hailing. The study pointed to this as evidence of substitution, although with many surveyed ride hailing users stating they also used other transport modes on the same day, the overall impact of ride hailing was unclear. Similarly, Tang et al. (2019) found that many respondents in a survey of ride hailing users across Chinese cities stated they would have taken a taxi, public transport or private car in the absence of ride hailing, suggesting a substitution effect. Survey respondents in Boston with good access to public transport were more likely to replace public transport and thus increase the number of car trips (Gehrke et al., 2019). Shi et al. (2021a) showed that 16.8 per cent of respondents in a survey of ride hailing users in Chengdu, China increased travel frequency due to ride hailing, suggesting additional induced demand, but that around half of the respondents stated they had substituted ride hailing for public transport, cycling or walking. Evidence of substitution, with ride hailing replacing both public transport and taxis, was also found by Tirachini and del Río (2019) in a survey of residents of Santiago, Chile.

Many studies of ride hailing's effect on other transport modes have relied on cross-sectional data and, therefore, could not furnish the literature with any causal relationships. However, a difference-in-differences methodology has become popular in this literature, with several studies adopting this econometric approach in an effort to unearth causal effects of ride hailing on other transport modes (Zhong et al., 2022; Shi et al., 2021b; Paundra et al., 2020; Zhong et al., 2020; Ward et al., 2019; Hall et al., 2018; Guo et al., 2018, for example).

The Tirachini (2019) review found the relationship between car ownership and ride hailing to be disputed as well. In the US, Wang et al. (2021) found that relative to occasional users, regular ride hailing users tended to own fewer vehicles. Ward et al. (2019) found that the entry of ride hailing platforms into US states reduced vehicle registrations. Across Chinese cities, Guo et al. (2018) found a short-term increase in car sales due to the entry of DiDi, while Zhong et al. (2020) detected a negative impact on private car ownership. In Indonesia, Paundra et al. (2020) distinguished between a short-term negative impact, but a longer-term positive impact on new vehicle registrations. Drawing on survey data for Denver in the US, Henao and Marshall (2019) showed evidence that ride hailing was replacing driving trips to reduce demand for parking, while Henao and Marshall (2018) argued that ride hailing still led to an 83.5 per cent increase in vehicle kilometres.

Ride hailing could be regarded as a direct competitor of traditional taxis. Sure enough, Zhong et al. (2022) and Nie (2017) both showed negative impacts of ride hailing on the use of traditional taxis in China, and Contreras and Paz (2018) found a negative association between ride hailing and the use of traditional taxis in Las Vegas between 2010 and 2016.

The Tirachini (2019) review also highlighted literature on traffic externalities associated with ride hailing, including impacts on congestion and road safety. Tarduno (2021) used the departure of Uber and Lyft from Austin, Texas as a natural experiment to show that ride hailing had reduced traffic speeds by roughly 2.3 per cent, indicating a very modest travel time externality. Agarwal et al. (2019) exploited ride hailing driver strikes in New Delhi, Bangalore and Mumbai in India in a difference-in-differences analysis of the effect of ride hailing on congestion, and found that the absence of ride hailing on strike days reduced travel times in all three cities. This finding that ride hailing increases congestion suggests that ride hailing is acting as a substitute for more sustainable travel modes. Conversely, however, using congestion data across 130 cities in Europe, Fageda (2021) found that the presence of Uber reduced average congestion, suggesting that ride hailing may be substituting private cars rather than public transport.

The number of road traffic collisions typically increases with traffic volumes, and a ride hailing effect on traffic could therefore be felt in road safety outcomes. The review noted an emerging literature using difference-in-differences approaches to establish a causal relationship between ride hailing and road traffic collisions, particularly alcohol-related collisions, in which results remain very mixed (Tirachini, 2019). Barreto et al. (2021) found that Uber's entry reduced traffic-related fatalities by around 10 per cent, and traffic-related hospitalisations by approximately 17 per cent, in Brazilian cities between 2011 and 2016. Dills and Mulholland (2018) and Greenwood and Wattal (2015) also found reductions in drunk driving accidents and fatalities, while Brazil and Kirk (2016) found no effect.

A related literature to these studies has considered cross-elasticities between transport modes, or the demand effect on one mode when an attribute of another mode is changed marginally. This cross elasticity can depend on a mode's own-elasticity of demand, each mode's relative market shares, and a diversion factor (Dodgson, 1986). Fearnley et al. (2018) collated cross elasticity estimates for bus and rail from over 20 different sources, and while the review found low levels of substitution between modes, passengers were found to be more sensitive to time (such as in-vehicle time, waiting time) than fare variations when selecting a mode. Rose and Hensher (2013) analysed factors in the demand for taxi services in Melbourne and developed choice models to derive cross elasticities for taxis.

1.4. How has regulation responded to ride hailing?

It should be noted that the rise of ride hailing has not been without controversy. Ride hailing has faced accusations of being unsafe, of reducing employment stability, and of disregarding the law in some cities (Hall et al., 2018). TNCs providing ride hailing emerged in a grey area of the regulatory environment, with regulation forced to catch up over time. This is in contrast with traditional taxis with whom ride hailing competes, which operate in a much more regulated environment. DiDi has been operating in China since 2012, but was only formally regulated and licensed from 2016 (Shi et al., 2021b). In Austin, Texas, RideAustin began providing a ride hailing platform in May 2016 after Uber and Lyft had withdrawn from the city due to disputes over local regulations, representing an example of tensions arising from regulation attempting to catch up (Dias et al., 2019). When Cabify and Uber entered the market in Chile in 2012 and 2014 respectively, despite being illegal, they thrived as a result of weak law enforcement coupled with high demand for the platforms. The central government began a process of legalisation and regulation in 2016 following violent clashes between Uber drivers and taxi drivers, another indication of the tensions created by the rise of ride hailing (Tirachini and del Río, 2019). In addition, there have also been serious safety concerns in relation to ride hailing and ride sharing, for example with DiDi suspending its Hitch platform in the wake of two separate female passenger deaths (Shah et al., 2021). However, while these issues are important in providing context to ride hailing, this study focuses on the impact of ride hailing on the use of other transport modes rather than on regulation, accountability, and safety.

1.5. This study

There remains clear disagreement in the literature as to the impact of ride hailing on the use of other transport modes such as public transport, and it is this question that I focus on in this paper. This question is important in determining whether ride hailing is helpful in the transition to sustainable transport in cities. I contribute to this debate with an empirical analysis of the effect of the entry of Uber into the cities of Glasgow and Edinburgh in Scotland during 2015. In Section 2, I describe the difference-in-differences methodology I adopt using travel diary data from repeated cross sections of the Scottish Household Survey from 2012 to 2019. Results in Section 3 show that the availability of ride hailing increased the use of public transport by just under 75 per cent relative to driving a car in Glasgow, although this effect was not reflected in Edinburgh. The increase in public transport use in

Glasgow was more pronounced among respondents who were younger, male, and employed. Conclusions and policy implications are discussed in Section 4.

2. Methods

2.1. Theoretical framework

First, it is worth conceptualising the entry of a ride hailing platform into a city. Consider a general model of the market for taxis, based on the model proposed by Douglas (1972). To the discerning passenger, both time and money are valuable. In this model, therefore, for a given level of demand for journeys, demand for taxis is assumed to be a function of time and monetary cost:

$$Q = f_Q(w_m + w_p, P) \tag{1}$$

Specifically, demand for taxis Q is a function decreasing in the taxi fare P and decreasing in the sum of the time spent matching a driver to a passenger, w_m, and the pick-up time, w_p. These waiting times, in turn, are each functions of the number of vacant taxi vehicles, V, and the number of waiting passengers, $W = Qw_m$:

$$w_m = f_m(V, W), \quad w_p = f_p(V, W) \tag{2}$$

In the street hailing model of Douglas (1972), where matching occurs when a vacant taxi passes a passenger, the bulk of the waiting time is spent matching a passenger with a driver. Formally, the matching time is inversely proportional to the number of vacant vehicles while the pick-up time is close to 0 (Douglas, 1972).

$$w_m \propto \frac{1}{V}, \quad w_p \to 0 \tag{3}$$

Arnott (1996) instead specified a radio dispatch model, where matching occurs when a passenger sends a request to a central dispatch centre. In this alternative model, it is the pick-up time that contributes most to the waiting time. Formally, the matching time is close to 0 while the pick-up time is inversely proportional to the square root of the number of vacant vehicles (Arnott, 1996):

$$w_m \to 0, \quad w_p \propto \frac{1}{\sqrt{V}} \tag{4}$$

A ride hailing market could be thought of as being similar to the radio dispatch model of Arnott (1996), with an online platform taking the place of a central dispatcher. Compared with a human dispatcher armed with a telephone and radio system, the enhanced efficiency of the online matching platform could further reduce the matching time w_m towards 0. Moreover, the introduction of ride hailing in a city could also be viewed as an increase in the combined supply of vacant taxi and ride hailing vehicles V, particularly in settings where taxis are subject to regulation and licensing requirements. This would decrease both the matching time w_m and pick-up time w_p, and thus increase the combined demand for taxis and ride hailing. This represents the first hypothesis that was tested as part of this study:

Hypothesis 1. The introduction of ride hailing increased the proportion of journeys where the main transport mode was car as passenger or taxi.

To ensure that any such effect would not simply pick up a concurrent increase in the supply of traditional licensed taxis, I confirmed that the number of licensed taxi vehicles in each Glasgow and Edinburgh was largely static between 2012 and 2019 (Transport Scotland, 2020), see Appendix C).

Whether ride hailing helps or hinders the transition to sustainable transport hinges on another question: What impact did ride hailing have on the use of public transport (Tirachini, 2019)? Bates (2018) described the distribution and modal split (DMS) model that forms an integral part of the widely used four-step model of transport demand. Bates (2018) outlined how the DMS model typically took the form of a conditional indirect utility function:

$$U_{j,m|i} = \log(A_j) + \alpha_m + \beta_c C_{i,j,m} + \beta^m t \left(t^1_{i,j,m} + \sum_2^k w_k t^k_{i,j,m} \right) + \varepsilon_{i,j,m} \tag{5}$$

Equation 5 describes a function of the indirect utility $U_{j,m|i}$ derived from travelling to destination j using transport mode m, conditional on the journey starting in origin i. The attraction of destination j is measured by A_j, while α_m represents a constant for mode m. The monetary cost of the journey from i to j using mode m is given by $C_{i,j,m}$, while time is denoted by t. Specifically, the time spent travelling on the journey's main mode m is given by $t^1_{i,j,m}$, while all other travel time components numbered 2 to k are denoted by t^k and weighted by w_k. These other time components may include time spent walking to a bus stop, getting another secondary mode to the bus stop, or waiting at the bus stop, for example. Based on the law of demand, the β coefficients on cost and time would all be expected to be negative (Bates, 2018).

The introduction of ride hailing in a city could be viewed as having the potential to reduce the overall time cost associated with a journey where the main mode is public transport. By acting as a secondary transport mode in a public transport journey, ride hailing could reduce the t^k that represents the time spent travelling to or from the nearest bus stop or train station. This is the essence of the last-mile argument made by Stiglic et al. (2018). If this were the case, ride hailing could be expected to have a complementary effect on public transport, and this was the second hypothesis tested in this study:

Hypothesis 2. The introduction of ride hailing increased the proportion of journeys where the main transport mode was public transport.

Alternatively, however, the introduction of ride hailing in a city could be regarded as the development of a mode of transport that competes with public transport to be chosen as the main mode for journeys. If ride hailing reduces the time or monetary cost associated with getting a taxi, this would increase the relative time t or monetary cost C associated with public transport. If this were true, ride hailing could be expected to act as a substitute for public transport.

Hypothesis 3. The introduction of ride hailing decreased the proportion of journeys where the main transport mode was public transport.

Increased road congestion is a possible externality that has been associated with ride hailing (Tirachini, 2019). Drivers sign up to ride hailing platforms with their private cars to supply journeys, and while an increase in vacant vehicles V in Equation 4 may reduce the pick-up time w_p, it may also represent an increase in the total number of motor vehicles using a city's road network. Agarwal et al. (2019) analysed travel times to assess the effect of ride hailing on congestion. A final hypothesis that could be tested in the present study stemmed from this:

Hypothesis 4. The introduction of ride hailing reduced the average journey speed of road-based journeys.

All four hypotheses were tested against the null hypothesis of ride hailing having no impact on either the choice of main mode for journeys or average journey speed respectively. Of course, to uncover any causal effects, an identification strategy was required to overcome issues related to unobserved confounding variables.

2.2. Study design

The causal relationship I explored in this study was the effect of ride hailing availability from 2015 on the use of other transport modes in Glasgow and Edinburgh. An ideal experiment to reveal this effect might have been to randomly allocate the population of each city into two groups, one that could avail of ride hailing and one that could not, and to compare changes in mode choice between the groups. However, as such an experiment was clearly not feasible, an alternative strategy to identify this causal relationship using applied microeconometric methods was required.

To test Hypotheses 1 to 3, following several studies in this literature (Zhong et al., 2022; Shi et al., 2021b; Paundra et al., 2020; Zhong et al., 2020; Ward et al., 2019; Hall et al., 2018; Guo et al., 2018), I employed a difference-in-differences methodology to identify any causal relationships between the presence of ride hailing platforms and the use of other transport modes. This method essentially involved comparing the average change over time between 2012 and 2019 in Glasgow and Edinburgh, where ride hailing became available, with the average change over time in two Scottish cities without ride hailing platforms, Dundee and Aberdeen. Specifically, I used the following regression design:

$$mode_{i,j,c,t} = \lambda_t + \gamma_c + \delta_c treated_{c,t} + X_{j,t} + \varepsilon_{i,j,c,t} \tag{6}$$

In Equation 6, the outcome variable $mode_{i,j,c,t}$ was a categorical variable recording the main mode of transport used for journey i, undertaken by individual j, in city c and year t. I specified driving a car or van as the reference category of this outcome variable for the purposes of the regression. Year fixed effects were accounted for by λ_t, while city fixed effects relative to the control group were captured by γ_c. I also included a vector of individual control variables $X_{j,t}$, namely gender, age group, education and household income, in this specification. The parameter of interest was δ_c, as this was the difference-in-differences parameter on a $treated_{c,t}$ categorical variable, which specified whether the journey occurred in 2016 or later and either started or ended in Glasgow or Edinburgh. This specification allowed the estimation of two separate treatment effects, one for Glasgow and one for Edinburgh, but assumed a constant treatment effect within each city.

Given the nominal, categorical nature of the outcome variable $mode_{i,j,c,t}$, I estimated

Equation 6 as a multinomial logistic regression using maximum likelihood. The advantages and disadvantages of the multinomial logistic regression, and its application to mode choice, were discussed by McFadden (1973), and McFadden (1974) employed a multinomial logistic regression in modelling urban travel demand. A multinomial logistic regression is a generalisation of a logistic regression that can be used to predict probabilities of different outcomes of a categorical variable with more than 2 possible discrete outcomes, given independent variables. Generally, given an outcome variable with 3 categories and vectors of control variables X and corresponding coefficients β, a multinomial logistic regression involves estimating a set of coefficients $\beta^{(1)}$, $\beta^{(2)}$ and $\beta^{(3)}$ for each possible outcome. To identify this model, it is necessary to arbitrarily set one outcome as the reference outcome. If $y = 1$ is set as the reference outcome such that $\beta^{(1)} = 0$, the multinomial logistic regression model includes the following equations:

$$\begin{aligned} \Pr(y=1) =& \frac{1}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}} \\ \Pr(y=2) =& \frac{e^{X\beta^{(2)}}}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}} \\ \Pr(y=3) =& \frac{e^{X\beta^{(3)}}}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}} \end{aligned} \tag{7}$$

The relative probability of $y = 2$ can then be derived from this model:

$$\frac{\Pr(y=2)}{\Pr(y=1)} = e^{X\beta^{(2)}} \tag{8}$$

This relative probability is known as the ‘relative risk ratio’. Returning to my study design summarised in Equation 6, a relative risk ratio for a given transport mode indicates how the ‘risk’ of that mode being chosen as the journey’s main mode, relative to the risk of it being the reference mode, changes with a one-unit change in the respective independent variable, controlling for all other included independent variables.

Therefore, for a given transport mode, a multinomial logistic regression estimate for δ_c in

Equation 6, denoted $\hat{\delta_c}$, would show the change in the multinomial log-odds of that mode being chosen over the reference transport mode (which I set as driving a car, the most common mode) due to ride hailing becoming available in city c. It is easier to interpret this coefficient when exponentiated (in other words, as the relative risk ratio), as the transformation $e^{\hat{\delta_c}} - 1$ is a percentage change in the relative probability of the respective mode being chosen over the reference mode. On this basis, I report all multinomial logistic regression results as exponentiated coefficients. For example, when examining results for the public transport category, a relative risk ratio that is greater than 1 tells us that an increase in the respective independent variable is associated with the chosen transport mode becoming more likely to be public transport. The standard errors reported for these exponentiated coefficients were transformed using the delta rule.[2] For each multinomial logistic regression, I also report McFadden's pseudo-R squared.[3] Untransformed regression coefficients and associated standard errors are also provided in Appendix B for all multinomial logistic regressions.

As individuals typically select a transport mode from a range of options, the multinomial logistic regression was a more appropriate specification for mode choice than a binary logistic regression. Of course, as a decision, mode choice is also intertwined with destination choice. The DMS model specified in Equation 5 collapses to a multinomial logistic regression only as long as no partition between mode and destination choice is assumed and a Gumbel distribution is assumed for the random term $\varepsilon_{i,j,m}$ (Bates, 2018). However, Bates (2018) highlighted the nested logit model as a more appropriate way of combining these decisions for the purposes of forecasting transport demand, with either mode or destination choice assumed to be conditional on the other. In addition to individual-level characteristics, a nested

[2]Specifically, the transformed standard error associated with an exponentiated multinomial logistic regression coefficient $e^{\hat{\delta_c}}$ was estimated as $e^{\hat{\delta_c}} \times SE(\hat{\delta_c})$.

[3]This is calculated as $1 - \frac{ll(model)}{ll(null)}$, where ll denotes log likelihood, and is not a direct equivalent of the R squared statistic calculated for OLS regressions.

logit of mode and destination choice would have required year-specific characteristics about each possible mode, such as mode cost or mode quality, and each possible destination. These variables were not available to this study without making strong simplifying assumptions, and the multinomial logistic regression approach was thus preferred. Rather than seeking to forecast travel demand, the aim of this study was specifically to assess the affect of ride hailing on the use of other transport modes.

Instead, the multinomial logistic regression required an assumption known as 'independence of irrelevant alternatives' (IIA), which imposed that the odds of selecting one mode over another did not depend on the presence or absence of other alternative modes. As discussed by Hausman and McFadden (1984), this essentially did not allow for any substitutability or complementarity between different choices. I conducted a post-estimation Hausman-McFadden test (Hausman and McFadden, 1984) to test the validity of this assumption. This involved re-estimating parameters with one of the outcomes excluded from the model and conducting a Hausman specification test (Hausman, 1978) comparing the two sets of coefficients, with a systematic difference between coefficients indicating a breach of the IIA assumption.

As established in setting Hypothesis 4, another potential aspect to the impact of ride hailing on other transport modes is the effect on congestion. Similar to Agarwal et al. (2019), I utilised a difference-in-differences approach to detect any causal impact on average journey speed as a measure of congestion, in this case by fitting a linear regression specification using ordinary least squares (OLS):

$$speed_{i,j,c,t} = \lambda_t + \gamma_c + \delta_c treated_{c,t} + X_{j,t} + \varepsilon_{i,j,c,t} \tag{9}$$

The outcome variable in Equation 9, $speed_{i,j,c,t}$, was a continuous variable measuring the average speed in kilometres per hour of journey i, undertaken by individual j, in city c and year t. I calculated this variable as the journey distance divided by the journey duration. The right-hand-side of Equation 9 was the same as in Equation 6. I also ran two further linear regressions with journey distance and journey duration as the outcome variables instead of journey speed.

I report linear regression results for treatment effect estimates as regression coefficients. These coefficients show the change in the outcome variable, for example speed in kilometres per hour, as a result of ride hailing becoming available, again controlling for all other independent variables.

The crucial identifying assumption in the difference-in-differences design in Equations 6 and 9 is that the outcome in the absence of treatment can be captured with an additive structure that includes a city component that does not change over time, and a time component that does not change across cities, conditional on control variables. In Equations 6 and 9, these components were represented by γ_c and λ_t respectively. This is known as the parallel trends assumption. In other words, identification relies on trends in the outcome variable being the same in the treatment and control groups if the treatment did not occur, conditional on control variables and once the fixed effects are accounted for. This essentially allows the trend in the control group to be employed to impose a counterfactual trend on the treatment groups, with a treatment effect identified as a deviation from this counterfactual trend.

This assumption would fall down if ride hailing became available in Glasgow and Edinburgh, but not Dundee or Aberdeen, due to some time-varying factor specific to Glasgow and Edinburgh. It is most likely, however, that Glasgow and Edinburgh were chosen by ride hailing companies simply due to them being larger population centres. To support this, Hall et al. (2018) referenced discussions with executives from Uber, in addition to aggregate data, indicating that Uber chose to enter cities in the US in order of population size. As shown in Figure 2, while all four cities in Scotland experienced a small increase in population between 2012 and 2019, the cities of Glasgow and Edinburgh boast much larger populations. The general population increase over time would have been accounted for by λ_t, and time invariant population differences across cities by γ_c, in Equations 6 and 9. It should also be noted that in this difference-in-differences design, identification was based solely on temporal variation (ride hailing only being available after 2015), in which case the possibility of an omitted variable bias could not be entirely ruled out. In Appendix C, however, I also discuss transport infrastructure in each of the 4 cities in my study setting, in addition to changes in fuel prices over my study period.

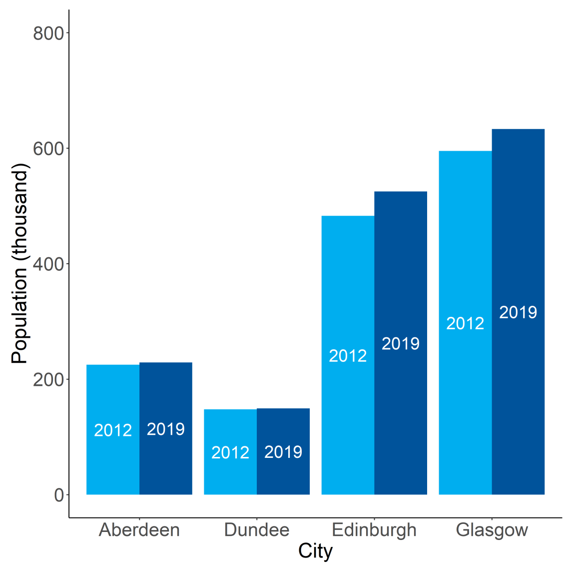


Figure 2: Population by city, 2012 and 2019. Sources: Author's analysis; Office for National Statistics (2020).

A regression represents a convenient way of conducting a difference-in-differences analysis, as it allows for the calculation of standard errors and can also facilitate the inclusion of control variables if required. Issues can arise with the calculation of standard errors in a difference-in-differences setting, however, as discussed in detail by Bertrand et al. (2004). One potential problem that may be relevant to my study design is that there may have been common unobserved factors that affected all journeys i made by the same individual j. A common solution suggested by Bertrand et al. (2004) is to cluster standard errors. When running the regressions described in Equations 6 and 9, I therefore clustered standard errors at the individual level j. This allowed for error terms to be correlated between journeys recorded by the same individual, albeit at the possible expense of precision. I assessed the merits of this approach by comparing standard errors calculated using various variance estimators (see Appendix B). Another possible problem is that my treatment variable, $treated_{c,t}$, changed very little over time within a city, and this could have produced serial correlation. However, in this case, clustering at the city level c with only 4 cities would likely lead to bias in calculating standard errors (Bertrand et al., 2004).

I conducted this regression analysis using Stata/MP 16.1.

2.3. Alternative specifications

To assess whether results were sensitive to the choice of combining Dundee and Aberdeen to construct a control group, I ran my main difference-in-differences regression (Equation 6) again using only Dundee-based journeys as the control group, and then using only journeys based in Aberdeen as the control group. Each of these alternative regressions involved dropping journeys based in the other city from the sample, thus reducing sample size in addition to altering the control group.

A common diagnostic in studies seeking to make causal inference is a 'placebo' test, or falsification test, which involves testing for the presence of the effect being studied in a setting where it should not occur. If I detected a ride hailing 'effect' among journeys in settings where ride hailing did not become available, this would raise serious concerns about the integrity of the key parallel trend assumption and thus about inferring causality. I conducted a placebo test by running my main difference-in-differences regression (Equation 6) again, maintaining Dundee and Aberdeen as the control group, but with journeys based in Glasgow or Edinburgh replaced with all non-city journeys that had been dropped from my main sample. Therefore, this test compared the average change over time between 2012 and 2019 in all mainland non-city local authorities with the average change over time in the cities of Dundee and Aberdeen. As ride hailing never became available in these areas, no 'effect' should be detected in this test. This placebo test is a similar procedure to the 'control experiment' conducted by Duflo (2001) in a study of economic returns to education.

The parallel trends assumption underpinning the difference-in-differences methodology may also come unstuck if a city-specific pre-existing trend in the outcome variable is present. For example, if the proportion of journeys using public transport in Glasgow or Edinburgh was generally increasing prior to the entry of ride hailing, it would be difficult to properly disentangle any further increase due to ride hailing from this general trend. This is an issue with difference-in-differences that was discussed in detail by Wolfers (2006). One useful test for the presence of pre-existing trends is to additionally control for panel-specific trends (Angrist and Pischke, 2008). Angrist and Pischke (2008) highlighted a study of labour regulation in India by Besley and Burgess (2004) as an example of this difference-in-differences approach in econometric literature. Specifically, I applied the following design to a multinomial logistic regression model to assess the robustness of my main results to the inclusion of linear trends:

$$mode_{i,j,c,t} = \lambda_t + \gamma_{0,c} + \gamma_{1,c}t + \delta_c treated_{c,t} + X_{j,t} + \varepsilon_{i,j,c,t} \tag{10}$$

In Equation 10, the λ_t and $\gamma_{0,c}$ parameters still accounted for year and city fixed effects respectively and $X_{j,t}$ still represented a vector of individual-level controls, while $\gamma_{1,c}$ captured city-specific linear trends in the outcome variable. The difference-in-differences parameter was again δ_c on the $treated_{c,t}$ variable. In this specification, the identification of an effect derived from whether ride hailing led to deviations from existing city-specific trends. This represented a more restrictive version of Equation 6 due to the inclusion of linear trends, and was therefore expected to increase standard errors.

However, as Wolfers (2006) pointed out, controlling for linear trends in this manner is problematic in any context where the treatment effect might be dynamic. For example, if the effect of ride hailing on mode choice increased over time as more drivers registered with the ride hailing platform, controlling for a linear trend while not modelling this impact dynamically could result in the linear trend picking up the post-treatment pattern. While it is not clear that ride hailing has a dynamic rather than constant impact on mode choice, this cannot be ruled out and regression results based on Equation 10 should therefore be interpreted with caution.

Another method for testing the robustness of the parallel trends assumption in a difference-in-differences framework suggested by Angrist and Pischke (2008) is to include lags and leads of the treatment in a more generalised model, as was done by Duflo (2001) and Autor (2003) in econometric literature, for example. This involves estimating δ_c coefficients for different years, and these can then be plotted as an additional test of causality in the spirit of Granger (1969). Essentially, this method could furnish the study with some evidence on whether causes happened before consequences, rather than the other way around. Specifically, to further assess the robustness of my main results, I applied the following design to a multinomial logistic regression model:

$$mode_{i,j,c,t} = \lambda_t + \gamma_c + \sum_{\tau=0}^{3} \delta_{c,-\tau} treated_{c,t-\tau} + \sum_{\tau=1}^{3} \delta_{c,+\tau} treated_{c,t+\tau} + X_{j,t} + \varepsilon_{i,j,c,t} \tag{11}$$

In Equation 11, λ_t and γ_c again represented year and city fixed effects respectively and $X_{j,t}$ denoted a vector of individual-level controls. This time, rather than obtaining a single estimate for each constant δ_c, separate estimates for $\delta_{c,-\tau}$ were obtained for 4 years after ride hailing becoming available, and estimates for $\delta_{c,+\tau}$ were obtained for 3 years prior to the introduction of ride hailing. The set of $\delta_{c,-\tau}$ parameters are known as post-treatment effects, while the set of $\delta_{c,+\tau}$ parameters are known as anticipatory effects. As with Equation 10, this was a more data-intensive version of Equation 6, and was thus expected to produce higher standard errors.

If there was an effect of ride hailing on mode choice and the parallel trends assumption held, post-treatment effect coefficients should be statistically significant while anticipatory effect coefficients should not be significant. In other words, there should only be evidence of an effect once ride hailing was available, assuming individuals were not altering their mode choices in anticipation of ride hailing becoming available. While this form of Granger causality test is still not conclusive in definitively proving causality, it can provide confidence in the parallel trends assumption (Angrist and Pischke, 2008).

2.4. Data

In this study, I employed data from the Scottish Household Survey (SHS) for each year from 2012 to 2019. This granular data offered a comprehensive picture of journeys undertaken by a representative sample of individuals over an 8-year period in cities with and without access to ride hailing, in addition to a detailed account of the socio-demographic characteristics of these individuals.

The SHS is an annual, cross-sectional survey of the characteristics, attitudes and behaviours of households and individuals across Scotland. The primary objective of the survey is to make representative estimates for the country. Each year, the survey targets a large sample size of 10,450 households, with a minimum of 250 households in each local authority to facilitate an analysis of all local authority areas. The Royal Mail's (UK postal service) Postcode Address File is used as the sample frame for address selection, and addresses selected for the survey are then removed from the sample frame for a period of at least 4 years (SHS, 2020).

The survey is conducted primarily via computer assisted personal interviewing (CAPI), which involves face-to-face interviews in respondents' homes that are supported by a computer. The first component of the interview, which captures data on the composition and characteristics of the household, is completed by the highest income householder or their partner. The second component is completed by a random adult in the household (aged 16 or over), and this gathers information on the attitudes and experiences of the random adult. For each annual survey during the 2012-2019 period, fieldwork for the survey was completed between January and either February or March (SHS, 2020).

I sourced journey data from the travel diary component of the SHS, which is completed by the random adult. During the CAPI interview, the random adult is requested to complete a diary of their travel behaviour during the day prior to the interview. Any journeys undertaken by the random adult over the course of the day are recorded, including details of the start and end local authority area, the main mode of transport used, any other modes used during different stages of the journey, the purpose of the journey, and the journey distance and duration (SHS, 2020).

In total, 152,219 journeys were recorded in this manner by the SHS during the 2012-2019 period. To focus the analysis on the four main cities in Scotland, I reduced this to a sub-sample of 43,169 journeys that either started or ended in the local authority areas of Glasgow City, City of Edinburgh, Dundee City or Aberdeen City. Further details on how I reduced the sample size are provided in Appendix A. An illustration of these journeys by local authority area is presented in Figure 3, and descriptive statistics for journey transport modes and journey purposes are provided in Table 1.

These journeys were spread across 16,712 respondents, implying that on average, each random adult recorded 2.6 journeys in the travel diary. The socio-demographic characteristics, including age, gender and economic status, of these random adults are summarised in Table 2.

The socio-demographic characteristics of the random adults were broadly similar between

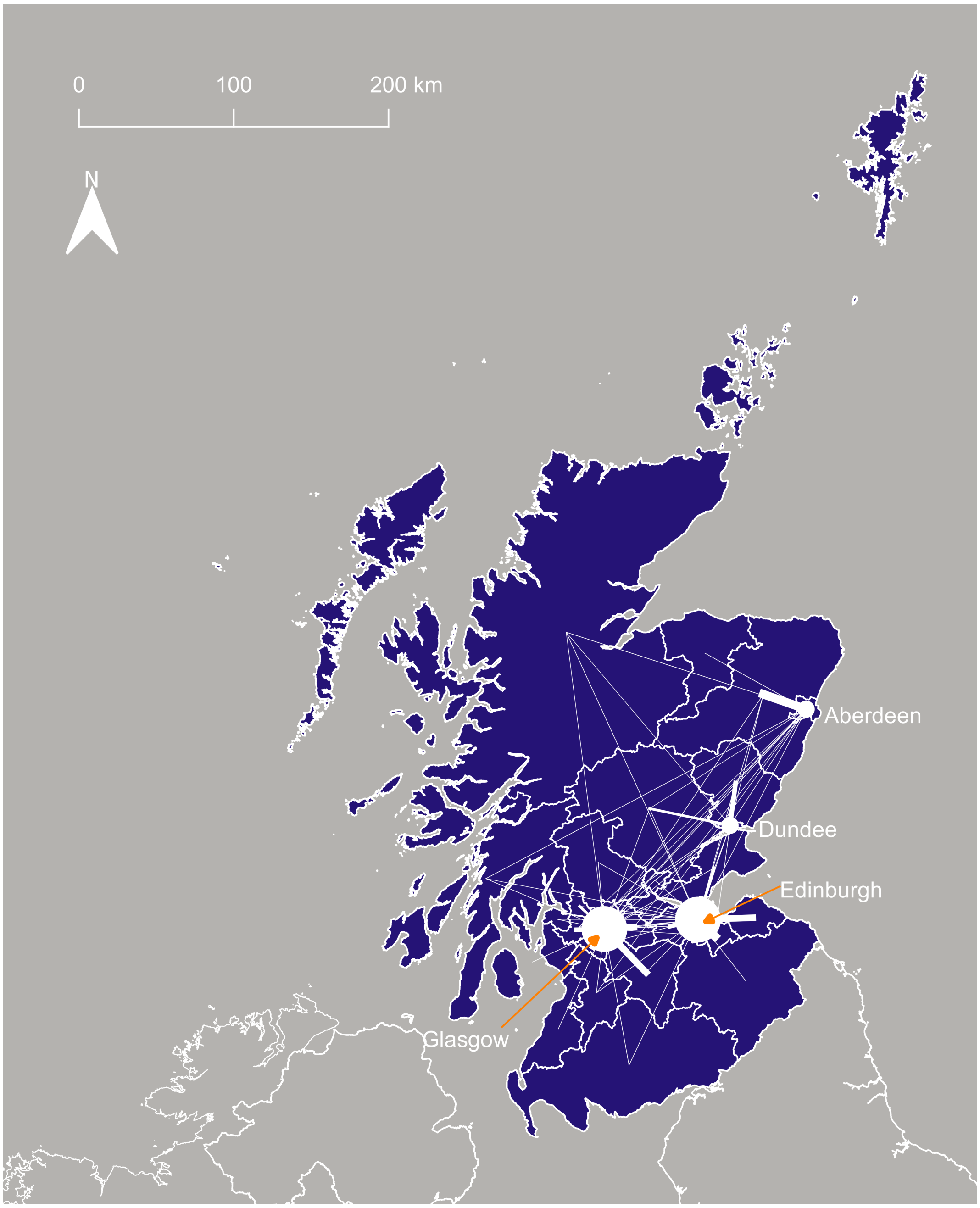


Figure 3: Journeys starting or ending in Edinburgh, Glasgow, Dundee or Aberdeen, 2012-2019. Line weight is defined by the number of journeys between two local authorities. Point size is defined by the number of journeys within a city. Source: Author's analysis; SHS (2020).

the control group and each Glasgow and Edinburgh, with a higher level of education evident in Edinburgh (see Appendix B). I also compared distributions of age and household

Table 1: Descriptive statistics of included journeys, 2012-2019

Variable	Category	Count	Percentage
Main mode	Car as driver	18786	43.52
	Public transport	7096	16.44
	Car as passenger	5029	11.65
	Walk	10431	24.16
	Other	1827	4.23
Journey purpose	Work	11224	26
	Education	2438	5.65
	Shopping	9900	22.93
	Health	1116	2.59
	Leisure	8526	19.75
	Returning home	5258	12.18
	Going for walk	1510	3.5
	Other	3197	7.41
Total		43169	100.00

Car as passenger includes taxi.
Sources: Author's analysis; SHS (2020)

income between the control groups and each treatment group, further indicating largely similar demographic and socio-economic characteristics (see Appendix B). Any time invariant, city-specific socio-demographic factors that affected my outcome variables were picked up by γ_c in Equations 6 and 9. I ran t-tests of differences between 2012 and 2019 in socio-demographic characteristics of the random adults in each group to determine whether any of these factors were time-varying (see Appendix B). Household income increased in each group over the period, and there was also evidence of increasing education levels in Glasgow and the control group. General time-varying socio-demographic factors that were not city-specific and that affected my outcomes were accounted for by λ_t in Equations 6 and 9. The t-tests revealed a 6 per cent increase in the average age among random adults making journeys to or from Edinburgh that was not reflected in Glasgow or the control group. The inclusion of individual-level control variables, including age group, helped account for this Edinburgh-specific increase.

Surveys that aim to glean information about a target population will typically apply

Table 2: Descriptive statistics of included random adults, 2012-2019

Variable	Category	Count	Percentage
Age group	16-24 years	1679	10.05
	25-44 years	6097	36.48
	45-64 years	5602	33.52
	65+ years	3291	19.69
	Missing	45	0.27
Gender	Male	7847	46.95
	Female	8822	52.78
	Missing	45	0.27
Economic status	Self-employed	979	5.86
	Employed	9063	54.22
	Looking after home/family	649	3.88
	Retired	3610	21.6
	Unemployed	563	3.37
	In education	1156	6.92
	Not working due to illness/injury	583	3.49
	Other	66	0.39
	Missing	45	0.27
Marital status	Never married	6546	39.16
	Married	6645	39.76
	Separated	544	3.25
	Divorced	1640	9.81
	Widowed	1293	7.74
	Missing	46	0.28
Highest education	Secondary, National	2601	15.56
	Secondary, Higher	2609	15.61
	Further education	1836	10.98
	Degree or higher	6651	39.79
	Other	823	4.92
	No qualification	2149	12.86
	Missing	45	0.27
Household income	£0-10,000	1841	11.01
	£10,000-20,000	4618	27.63
	£20,000-30,000	3468	20.75
	£30,000-40,000	2298	13.75
	£40,000-50,000	1689	10.11
	>£50,000	2197	13.14
	Missing	603	3.61
Total		16712	100.00

Highest education and total household annual net income measured at household level.
Sources: Author's analysis; (SHS, 2020)

survey weights to collected data to account for response rate differences between groups and for unequal selection probabilities. When making inferences about the population of

Scotland, the SHS (2020) applies survey weights at the household, random adult and travel diary level. Throughout my difference-in-differences analysis, I applied travel diary weights to journeys. During fieldwork for all cross sections of the SHS (2020), disproportionately fewer interviews were conducted on Friday, Saturday and Sunday, and disproportionately more adults in full-time employment were interviewed over the weekend. Based on this, to calculate travel diary weights, the SHS (2020) rescaled the random adult weights to ensure travel diaries were representative of travel patterns over the entire week and of working status across each day of the week (see SHS (2020) for further details). As a robustness check, I also assessed whether my results were sensitive to the inclusion of these travel diary weights.

It is worth noting that as with any self-reported data, my outcome variables were likely subject to a small degree of measurement error. For example, respondents may have inaccurately recalled some details of their travel patterns, although this possibility was minimised by travel diaries being recorded for the day immediately prior to the interview. Alternatively, it is possible that respondents could have deliberately omitted or misrepresented some information on their travel patterns. The possibility of small errors in capturing travel diary data cannot be ruled out either, although the use of CAPI would have minimised this risk. Such measurement error would have increased noise in my regression specifications, making the detection of any true effect more difficult.

2.5. Outcome variables

My main outcome variable of interest was the main mode of transport used for the recorded journey (see Equation 6). I collapsed this into a five-category variable (see Appendix A for details) for the purposes of this empirical analysis, for example by combining bus and train categories into a public transport category. Category frequencies are included in Table 1, and Figure 4 illustrates this modal split by destination city. As shown in Figure 4, driving a car boasted the largest share of journeys across all four cities, with walking the second largest across all cities.

I also employed average journey speed, as well as journey duration and journey distance, as outcome variables (see Equation 9). For each recorded journey, the respondent specified the distance of the journey in kilometres and the duration in minutes. These variables were available as continuous variables in the SHS (2020) data. I calculated average journey speed as the distance divided by the duration and converted this speed to kilometres per hour. Descriptive statistics for these three variables are provided in Table 3.

Table 3: Descriptive statistics for continuous variables of included journeys 2012-2019

	N	Mean	S.D.	Min.	Max.
Journey distance (km)	43,169	7.07	9.49	0.00	57.33
Journey duration (mins)	43,169	21.96	15.19	1.00	70.00
Journey average speed (km/h)	43,169	17.14	15.71	0.00	207.98

N denotes observations. S.D. denotes standard deviation
Sources: Author's analysis; SHS (2020)

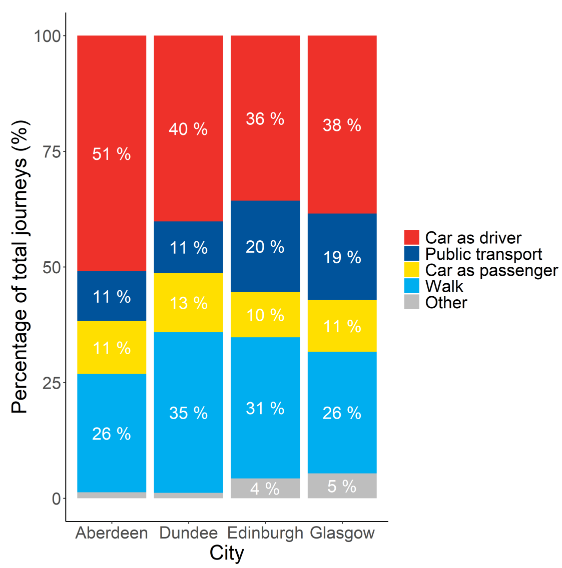
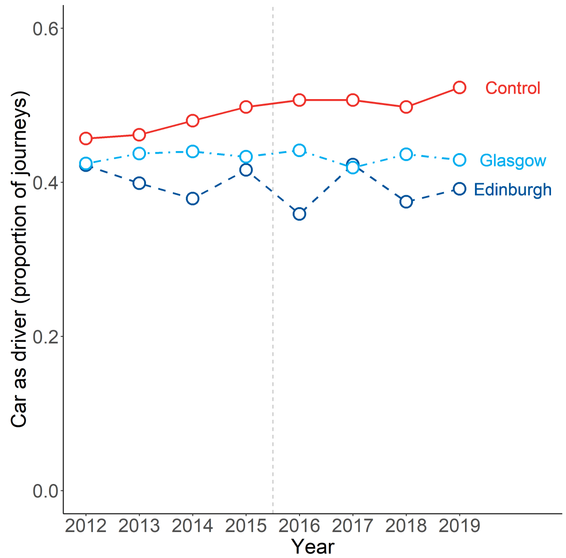
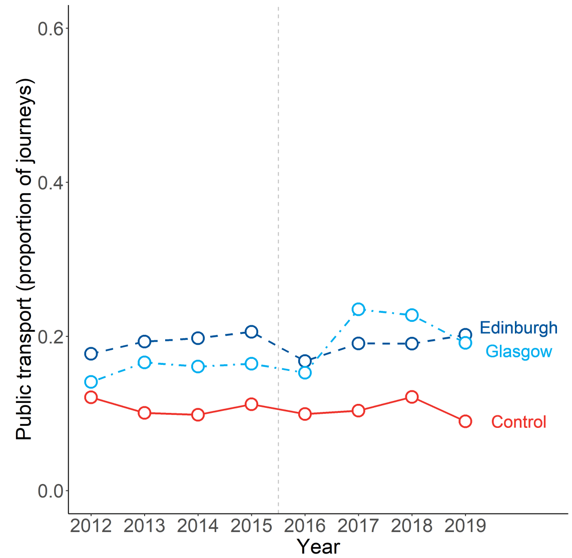


Figure 4: Journey main mode choice by city, 2012-2019. Car as passenger includes taxi. Other includes bicycle, motorcycle/moped, ferry, air, horse-riding and tram. Sources: Author's analysis; SHS (2020).

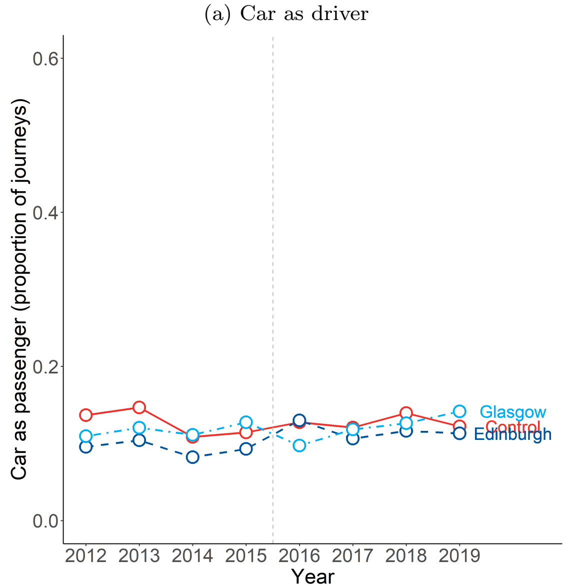
My difference-in-differences methodology compared the average change over time between



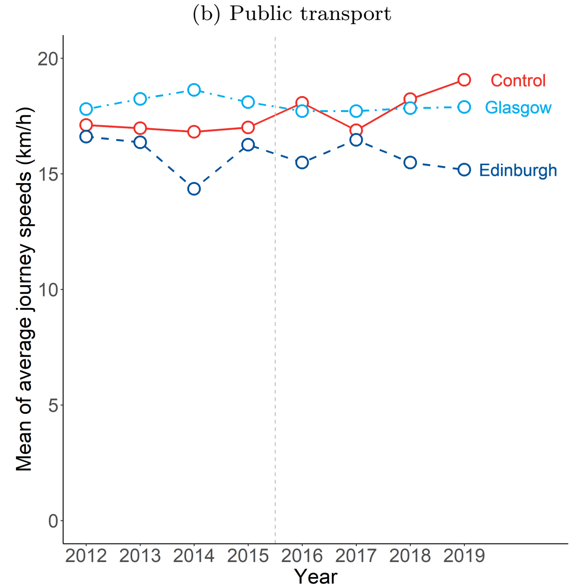
(a) Car as driver



(b) Public transport



(c) Car as passenger



(d) Mean of average journey speeds

Figure 5: Journey main mode choice and mean of calculated average journey speeds, 2012-2019. Control group comprised of Dundee and Aberdeen. Ride hailing became available in Glasgow and Edinburgh between 2015 and 2016 surveys (grey dashed line). Sources: Author's analysis; SHS (2020).

2012 and 2019 in Glasgow and Edinburgh with the average change over time in the control group comprised of Dundee and Aberdeen. Figure 5 illustrates the proportion of journeys where the main transport mode was car as driver, public transport and car as passenger[4], as well as the mean of my calculated average journey speeds, by year for each Glasgow and Edinburgh and the combined control group of Dundee and Aberdeen. One of the most striking dynamics across these outcomes was a dramatic increase in the proportion of journeys where public transport was the main mode in Glasgow between 2016 and 2017, relative to a much smaller increase in the control group. This may indicate a treatment effect from the introduction of ride hailing that was delayed by around a year, as Uber launched in Glasgow in late 2015. Figure 5 also suggests a decrease in average journey speeds (and, by extension, an increase in congestion) in Glasgow and Edinburgh in more recent years that was not reflected in the control group.

These raw differences in mean outcomes were worthy of further examination in a difference-in-differences framework.

2.6. Difference-in-differences variables

I assigned each of the 43,169 journeys i that started or ended in Glasgow, Edinburgh, Dundee or Aberdeen to a single city c. First, if the journey started in one of the cities, I assigned the journey to that city. For example, journeys from Glasgow to Edinburgh or from Glasgow to the local authority area of East Dunbartonshire were assigned to Glasgow. Second, for the remaining journeys that started from a non-city local authority area but ended in one of the cities, I assigned the journey to that city. For example, a journey from the local authority area of Fife to Edinburgh was assigned to Edinburgh. Figure 6 illustrates the percentage of journeys assigned to each city following this approach.

Once journeys were assigned to cities, the next task involved the generation of a treatment variable. Uber entered Glasgow and Edinburgh to provide a ride hailing platform during

[4] As shown in Appendix A, I collapsed the 'Taxi/minicab' category into the 'Car/van as passenger' category as the taxi category was simply too small to be reliable in my empirical analysis. In addition, it is possible that a ride hailing journey could be recorded in either of these two categories by respondents.

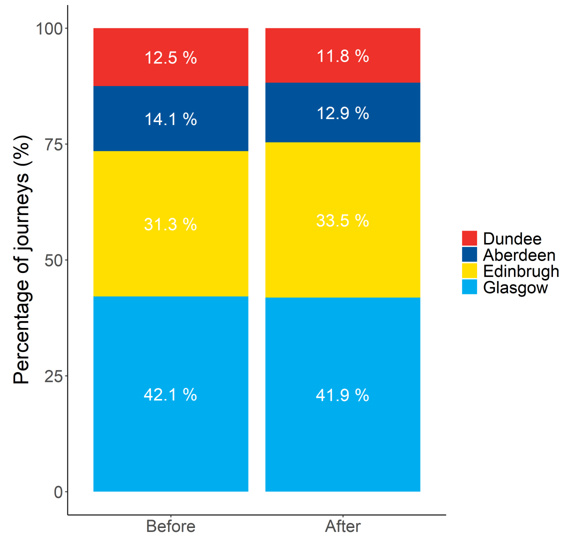


Figure 6: Percentage of journeys by assigned city, before and after availability of ride hailing. Sources: Author's analysis; SHS (2020).

October and November 2015, after the fieldwork for the 2015 cross section of the SHS was completed.[5] In the UK, all Uber drivers are required to have a private hire licence. Figure 7 depicts an increase in private hire car licences of 49.4 per cent in Glasgow and 129 per cent in Edinburgh between Uber's entry in 2015 and 2019. While this rise was not necessarily limited to the emergence of ride hailing, it represents descriptive evidence of the extent of Uber's increasing prevalence in both cities between 2015 and 2019. As of the end of 2019, a ride hailing platform had not entered either Dundee or Aberdeen, and the increase in private hire licences in Glasgow and Edinburgh was not reflected in these cities. Therefore, I considered journeys assigned to Edinburgh or Glasgow to represent my treatment groups, and my control group to consist of journeys assigned to Dundee or Aberdeen.

To allow for the estimation of treatment effects for each Glasgow and Edinburgh, I generated a categorical $treated_{c,t}$ variable. This variable was equal to 1 if the journey year

[5] Another ride hailing platform, MyTaxi (later Free Now), launched in Edinburgh in May 2018, by which time ride hailing was already available through Uber.

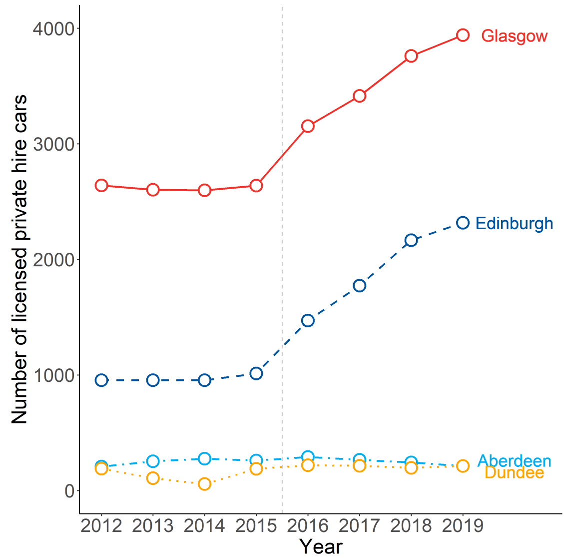


Figure 7: Number of licensed private hire cars by city, 2012-2019. Ride hailing became available in Glasgow and Edinburgh in late 2015 (grey dashed line). Source: Author's analysis; Transport Scotland (2020).

t was 2016 or later and the assigned city c was Glasgow, equal to 2 if the year t was 2016 or later and the city c was Edinburgh, and equal to 0 otherwise.

3. Results

3.1. Main transport mode

The first column of Table 4 presents summary results for my difference-in-differences multinomial logistic regression of the journey transport mode (Equation 6), with results reported as exponentiated regression coefficients, or relative risk ratios. Relative to driving a car (the reference category for my outcome variable), ride hailing increased the probability of public transport being used as the main transport mode in Glasgow by almost 75 per cent. This result was not reflected in Edinburgh, where the effect on public transport was positive but not statistically significant.

Taking a car as a passenger (including taxi journeys) became more likely than driving a car in Edinburgh as a result to ride hailing, although this was not reflected in Glasgow, and there was some evidence that walking became more likely relative to driving a car in both cities. In Glasgow, the 'other' category was much less likely to be chosen relative to driving a car as a result of ride hailing. This result is difficult to interpret given the miscellaneous nature of the category, which in any case only accounts for a small proportion of total journeys.

Table 4: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) Main	(2) Under 45	(3) Male	(4) Employed	(5) High income	(6) Degree
Public						
Treated Glasgow	1.749^{***}	1.898^{***}	2.315^{***}	2.074^{***}	2.987^{***}	1.807^{**}
	(0.242)	(0.398)	(0.486)	(0.392)	(0.960)	(0.465)
Treated Edinburgh	1.138	1.014	1.286	1.339	1.391	1.131
	(0.166)	(0.221)	(0.277)	(0.258)	(0.447)	(0.287)
Passenger						
Treated Glasgow	1.211	1.032	0.942	1.208	1.382	0.980
	(0.166)	(0.209)	(0.214)	(0.226)	(0.381)	(0.221)
Treated Edinburgh	1.450^{**}	1.162	1.515	1.280	1.589	1.271
	(0.220)	(0.264)	(0.389)	(0.266)	(0.480)	(0.316)
Walk						
Treated Glasgow	1.381^{***}	1.312	1.237	1.335^{*}	1.713^{**}	1.074
	(0.167)	(0.223)	(0.214)	(0.214)	(0.453)	(0.206)
Treated Edinburgh	1.385^{**}	1.194	1.330	1.276	1.379	1.288
	(0.177)	(0.214)	(0.243)	(0.203)	(0.361)	(0.237)
Other						
Treated Glasgow	0.424^{***}	0.610	0.751	0.415^{**}	0.677	0.297^{***}
	(0.134)	(0.233)	(0.282)	(0.160)	(0.505)	(0.135)
Treated Edinburgh	0.889	1.049	1.259	0.778	1.341	0.857
	(0.287)	(0.414)	(0.486)	(0.305)	(0.999)	(0.393)
Observations	43169	20290	19978	25805	10333	17758
Pseudo R^2	0.091	0.089	0.100	0.067	0.071	0.071
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes

Exponentiated coefficients; Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I ran this same regression (Equation 6) on various sub-samples of the data to assess whether there was any heterogeneity in effects by socio-demographic characteristics, and columns 2 to 6 of Table 4 provides results of this sub-sample analysis. This shows that the effect on public transport was more pronounced among younger respondents under the age of 45 (column 2) and male respondents (column 3). The effect was also stronger among respondents who were employed (column 4) and whose household held at least a degree (column 6). The result appeared to be strongest among respondents with a total annual net household income of greater than £30,000, with public transport more likely by almost 200 per cent because of ride hailing (column 5). The consistency of this result across all sub-samples represented evidence in favour of Hypothesis 2 (and against Hypothesis 3).

The result in relation to taking a car as a passenger for Edinburgh in my full-sample regression (column 1) was less clear as it was not reflected in most sub-samples. Therefore, there was insufficient evidence to reject the null in the case of Hypothesis 1. The results suggesting that walking became more likely, and 'other' becoming less likely, relative to driving a car in both cities were generally not reflected in my sub-sample analysis either.

I also conducted a sub-sample analysis to explore heterogeneity in results by journey purpose. Column 1 of Table 5 repeats the results of my full-sample regression, and columns 2 and 3 show results for sub-samples of work-related and leisure journeys respectively. The effect on public transport relative to driving a car in Glasgow was considerably more pronounced among work-related journeys, with the relative probability increased by 177 per cent, but statistically insignificant among leisure journeys. In addition, among work-related journeys, I detected a positive effect on the probability of using public transport in Edinburgh, with an increased relative probability of just under 91 per cent.

Table 5: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) Main	(2) Work	(3) Leisure
Public			
Treated Glasgow	1.749***	2.770***	1.387
	(0.242)	(0.656)	(0.395)
Treated Edinburgh	1.138	1.907***	0.775
	(0.166)	(0.462)	(0.224)
Passenger			
Treated Glasgow	1.211	0.969	1.568*
	(0.166)	(0.323)	(0.366)
Treated Edinburgh	1.450**	0.991	1.792**
	(0.220)	(0.384)	(0.457)
Walk			
Treated Glasgow	1.381***	1.124	1.650**
	(0.167)	(0.277)	(0.386)
Treated Edinburgh	1.385**	1.285	1.123
	(0.177)	(0.304)	(0.270)
Other			
Treated Glasgow	0.424***	0.456*	0.265**
	(0.134)	(0.211)	(0.143)
Treated Edinburgh	0.889	1.007	0.397*
	(0.287)	(0.474)	(0.222)
Observations	43169	11224	8526
Pseudo R^2	0.091	0.094	0.098
Year fixed effects	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes

Exponentiated coefficients; Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2. Average journey speed

Column 3 of Table 6 shows summary results for my difference-in-differences linear regression of average journey speed (Equation 9) using a sub-sample of road-based journeys, in addition to results for linear regressions of journey duration (column 1) and journey distance (column 2). I found some evidence of a negative effect on average journey speed, and by extension an increase in congestion, in Glasgow. Over the 2012-2015 period, before ride hailing became available, the mean of average journeys speeds was 18.19 and 15.87 kilometres per hour in Glasgow and Edinburgh respectively. Table 6 suggests that the introduction of ride hailing led to a reduction in average journey speed in Glasgow of 1.3 kilometres per hour, or 7.15 per cent, and represents some evidence in favour of Hypothesis 4. Again, however, this effect was not reflected in Edinburgh. I found no evidence of an effect on journey distance, but some evidence journey duration was longer by 1.23 minutes in Edinburgh due the introduction of ride hailing.

Table 6: Regression difference-in-differences estimates of ride hailing effect on journey duration, distance and speed

	(1) Duration	(2) Distance	(3) Speed
Treated Glasgow	0.142	-0.629	-1.296*
	(0.701)	(0.505)	(0.768)
Treated Edinburgh	1.231*	0.227	-0.096
	(0.744)	(0.520)	(0.792)
Observations	29732	29732	29732
Adjusted R^2	0.023	0.031	0.042
Year fixed effects	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes

Standard errors in parentheses
Robust standard errors clustered at individual level
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.3. Robustness

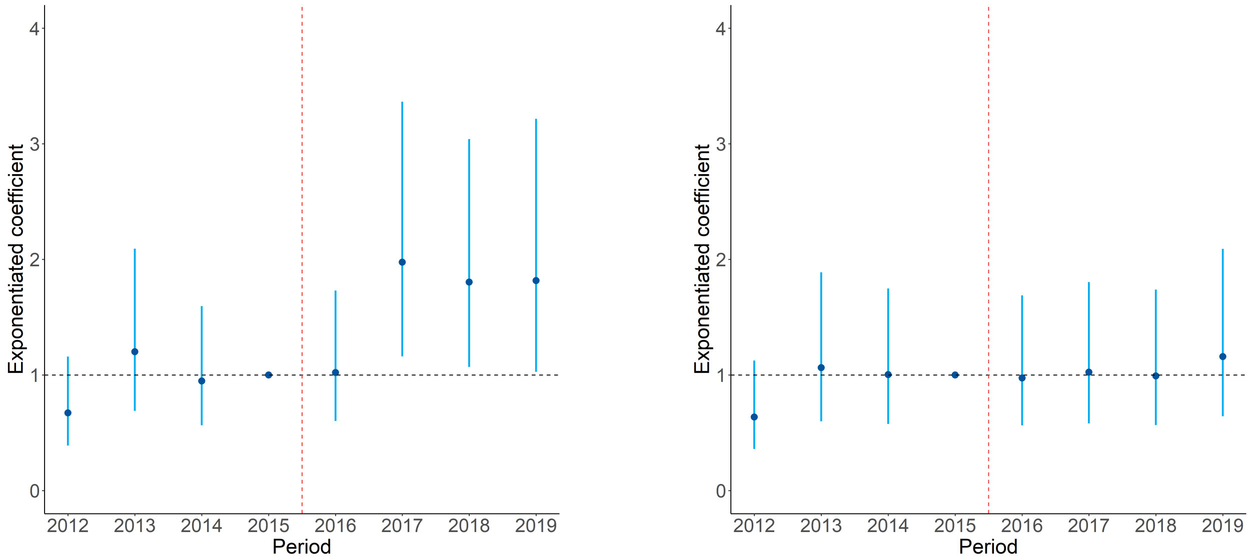
As shown in Appendix B, I determined that the ride hailing effect on public transport in Glasgow persisted when limiting the control group solely to journeys from Dundee, and solely to Aberdeen journeys. I also confirmed using a placebo test that no 'effect' could be detected among local authorities where ride hailing did not become available (see Appendix B). I also provide results of my alternative regression specification that included city-specific linear trends (Equation 10) in Appendix B. This regression tested whether my results in relation to public transport becoming more likely relative to driving a car were robust to the inclusion of city-specific linear trends. As expected, standard errors were increased due to the more restrictive specification. The public transport result did not hold in this specification, and was thus not robust to the inclusion of linear trends.

However, Figure 8 illustrates the exponentiated regression coefficients for the effect of ride hailing on public transport, relative to driving a car, in each Glasgow and Edinburgh from my more generalised model that included lags and leads of the treatment (Equation 11). This shows that in Glasgow, no treatment was detected in the years before ride hailing became available, while an effect was evident in each 2017, 2018 and 2019. In addition to suggesting that the effect on public transport in Glasgow was in fact robust and that the null hypothesis could be rejected in the case of Hypothesis 2, this provides reassurance that cause occurred before consequence rather than the other way around. It also suggests that it may have taken some time from the launch of Uber in late 2015 to produce an effect on other transport modes from early 2017 onwards, rather than there being an immediate effect.

In the case of Edinburgh, Figure 8 shows that there was no evidence of an effect on public transport, which is consistent with the weaker public transport results for Edinburgh in other regression specifications.

My results for average journey speed were not reflected in the generalised model of treatment lags and leads, as shown in Figure 9. While there was no evidence of anticipatory effects, I also found little evidence of post-treatment effects, indicating that the results in Table 6 cannot be considered robust. Based on this, there was insufficient evidence to reject the null for Hypothesis 4.

I conducted a Hausman-McFadden test (Hausman and McFadden, 1984) using my main regression specification of mode choice to assess the validity of the multinomial logistic model's IIA assumption. The results of this test were mixed. The test did not detect any

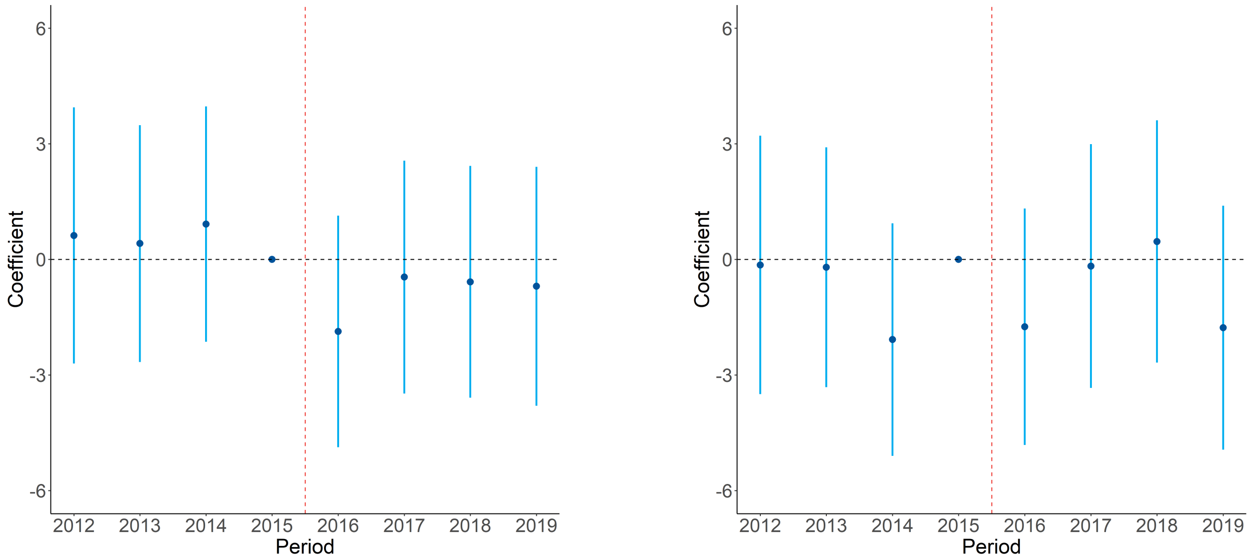


(a) Glasgow

(b) Edinburgh

Figure 8: Regression difference-in-differences estimates coefficients and 95 per cent confidence intervals for effect of ride hailing effect on public transport, generalised model 2012-2019. Exponentiated coefficients. Robust standard errors clustered at individual level and transformed using delta method. Uber operating in Glasgow and Edinburgh from 2016 onwards (red dashed line). Sources: Author's analysis; SHS (2020).

systematic difference between model coefficients when the public transport category was removed (Chi-squared = 91.91, p-value = 0.34), suggesting the IIA assumption held. However, a systematic difference was found when the car as passenger category was instead removed (Chi-squared = 130.94, p-value = 0.00), and this represented evidence that the assumption was breached. Based on this, I ran a further difference-in-differences regression of mode choice using a nested logistic model instead of a multinomial logistic model, having generated proxy variables for mode cost and mode quality based on some simplifying assumptions. The nested logit model relaxes the IIA assumption, and McFadden (1981) detailed how it can be derived from a rational choice framework. Reassuringly, I found that my main result of a complementary effect on public transport persisted in a nested logit model (see Appendix B for details and results of this analysis).



(a) Glasgow

(b) Edinburgh

Figure 9: Regression difference-in-differences estimates coefficients and 95 per cent confidence intervals for effect of ride hailing effect on average journey speed of road-based journeys, generalised model 2012-2019. Robust standard errors clustered at individual level. Uber operating in Glasgow and Edinburgh from 2016 onwards (red dashed line). Sources: Author's analysis; SHS (2020).

3.4. Mechanism

To dig deeper into this finding of a positive effect on the use of public transport, I ran my main regression specification (Equation 6) again with the mode choice outcome variable amended to split the public transport category into separate bus and rail categories. This tested whether the effect on public transport mainly affected bus journeys or rail journeys. Results for this regression, provided in Appendix B, indicated that the public transport effect stemmed from rail journeys, with significant positive effects found on the use of rail in both Glasgow and Edinburgh. Meanwhile, no effect was found among bus journeys in either city.

How could ride hailing complement public transport? I formed Hypothesis 2 on the basis that ride hailing could, by acting as a secondary mode of transport for a journey where the main mode was public transport, reduce the time spent travelling to or from the nearest train station or bus stop (Stiglic et al., 2018). Figure 10 thus compares the percentage of all public transport journeys that also involved the use of a car as a passenger, during another stage of the same journey, before and after the launch of ride hailing in Scotland in 2015. While this percentage was very small in both periods, it was perceptibly higher after 2015 at 1.4 per cent compared with 0.1 per cent before.[6] To test this difference, I ran a logistic regression of this percentage on a dummy variable that was equal to 1 if the journey occurred in 2016 or later, and 0 otherwise. I found a significant increase in the probability that a public transport journey also involved the use of a car as a passenger in the period after the launch of ride hailing (see Appendix B). This result cannot be interpreted as a causal effect as the number of journeys involving both public transport and a car as a passenger was too small to permit a difference-in-differences analysis, but it nonetheless provides some descriptive evidence on how ride hailing may have affected public transport.

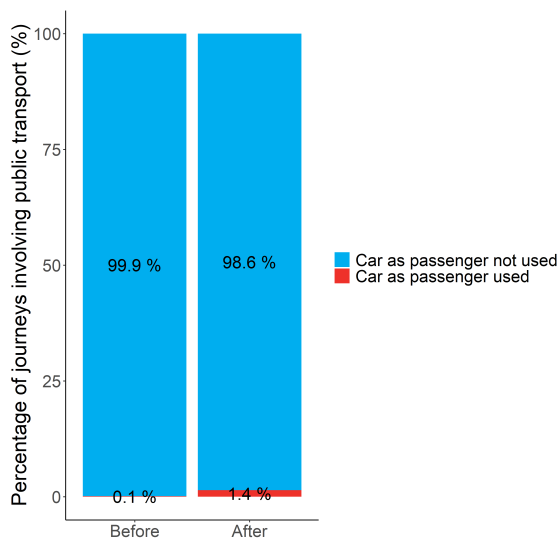


Figure 10: Use of car as passenger as journey stage among public transport journeys, before and after availability of ride hailing. Car as passenger includes taxi. Sources: Author's analysis; SHS (2020).

[6]Specifically among rail journeys, this percentage increased from 0 to 3.9 per cent.

4. Discussion

Ride hailing has been increasing in popularity over the past decade (see Figure 1), and yet a consensus in the literature as to its impact on the use of other transport modes remains elusive. Does ride hailing complement or substitute other forms of transport, such as public transport? This question is key to whether ride hailing should be viewed as helpful in transitioning to sustainable transport (Li et al., 2024; Tirachini, 2019; Hall et al., 2018). This paper contributes to this debate with an empirical analysis of the effect of the entry of Uber into the cities of Glasgow and Edinburgh in Scotland during 2015, using a difference-in-differences methodology and travel diary data from repeated cross sections of the SHS (2020) from 2012 to 2019.

The results of my difference-in-differences analysis revealed that the availability of ride hailing increased the use of public transport relative to driving a car in Glasgow. The magnitude of this effect was considerable, increasing the probability of using public transport by approximately 75 per cent relative to driving a car. There was insufficient evidence of this effect being reflected in Edinburgh, however.

I determined that the public transport result for Glasgow was not robust to the inclusion of city-specific linear trends in the regression model. This may have been a reflection of the issue discussed by Wolfers (2006), that controlling for linear trends may actually contaminate results in a setting where the treatment effect might be dynamic rather than immediate and constant. It is possible that as more drivers registered with the ride hailing platform (see Figure 7 for the post-2015 increase in licensed private hire cars in Glasgow and Edinburgh) and more passengers became aware of its availability, its effect on other transport modes increased. In a more generalised model that included treatment leads and lags to test for anticipatory and post-treatment effects, I found that a positive post-treatment effect on public transport was evident in Glasgow for each year other than the first year in which ride hailing was available, 2016. This result suggested that there was indeed a dynamic effect that took time to emerge rather than being immediate. This may explain why the result did not appear in my linear trends specification, as the linear trend could have soaked up some of this dynamic effect. I also found no evidence of anticipatory effects in Glasgow to provide reassurance that consequence occurred after cause rather than vice versa. In the case of Edinburgh, I found no evidence of anticipatory or post-treatment effects.

The public transport result for Glasgow represents evidence in favour of the argument that ride hailing has a complementary effect on public transport, in contrast with the finding of the Tirachini (2019) review that found a substitution effect to be more common among studies. Some studies on the effects of ride hailing on other transport modes have relied on cross-sectional data, however, and thus fell short of establishing causal relationships. The result is in line with Hall et al. (2018), who found a complementary effect of ride hailing on public transport using a difference-in-differences methodology with aggregate data from metropolitan areas in the US.

I found that the effect on public transport was more pronounced among respondents who were younger, male, employed and were members of a household that held at least a degree. The effect was particularly pronounced among respondents with higher levels of household income, with the probability of using public transport increased almost by almost 200 per cent among this sub-sample. These results were in line with the finding of the Tirachini (2019) review that ride hailing users tended to be younger, more highly educated and wealthier. They were also consistent with evidence provided by Sikder (2019) that individuals working full-time with flexible hours were more likely than non-workers to utilise ride hailing.

I then ascertained that the positive effect on public transport stemmed from an effect on rail transport, with no effect on bus transport found. This effect on rail was evident in both Glasgow and Edinburgh. This was consistent with a difference-in-differences study in China that found that ride hailing increased the number of rail passengers, but did not concur with its finding that ride hailing reduced the number of bus passengers (Shi et al., 2021b). The mixed results in the literature on the effect of ride hailing on public transport, as highlighted by Tirachini (2019), likely reflect different study settings, contexts and empirical methods. However, my finding that there was an effect on rail but not on bus transport, in addition to the findings of Shi et al. (2021b), indicate that public transport should not be treated solely as a homogeneous category in this literature.

There are several possible explanations for why ride hailing may have a complementary effect on public transport. While Tirachini (2019) found that ride hailing was predominantly used for occasional leisure trips, my results showed that the effect on public transport was stronger among work-related journeys, including either commutes or journeys undertaken in the course of work. Among these journeys, a positive effect of ride hailing on the use of public transport was found in both cities, rather than in Glasgow alone. Meanwhile, the result was not reflected in either city among journeys taken for leisure purposes in either city. These findings suggest that any mechanism for a positive effect on public transport resided in work-related rather than leisure journeys. This represents evidence in favour of the hypothesis discussed by Stiglic et al. (2018) and others that ride hailing has a complementary effect on public transport by helping to overcome the 'last mile' problem of connecting the home or workplace of individuals to the public transport network. Individuals may be utilising ride hailing to transport themselves between their home or workplace and the nearest train station, for example.

Based on this, I also showed evidence that the proportion of public transport journeys that also involved the use of a car as a passenger in a separate stage of the journey was higher after the introduction of ride hailing in Glasgow and Edinburgh. While there were not enough such journeys in my control group of Dundee and Aberdeen to establish this as a causal relationship, this increase at least offers some additional descriptive evidence to support the last mile theory. The increase in journeys combining public transport and car as passenger was significant in a logistic regression, but it should be noted that the increase was from a very low base, with 1.4 per cent of public transport journeys after the introduction of ride hailing, compared with 0.1 per cent before, also involving car as passenger.

What could explain the apparent differences in treatment effects between Glasgow and Edinburgh? In most specifications, while the estimated treatment effect for Edinburgh was positive, it could not be deemed statistically significant. While both cities are larger population centres than Dundee or Aberdeen (see Figure 2), population density and the density of transport infrastructure are higher in Glasgow, with 3,374 and 1,768 persons per square kilometre living in Glasgow and Edinburgh respectively in 2012 (Office for National Statistics, 2020, see Appendix C for further details). In addition, prior to ride hailing becoming available, the mean distance of Glasgow journeys was 7.41 kilometres compared with 6.77 kilometres for Edinburgh journeys among my SHS (2020) journeys. I showed in Figure 4 that while around 20 per cent of journeys in both Glasgow and Edinburgh were undertaken using public transport, driving a car was more popular in Glasgow than in Edinburgh, while walking was relatively more popular in Edinburgh. These figures suggest that Edinburgh is a smaller city that is more conducive to walking than Glasgow. The difference in treatment effects may indicate that there is more scope for ride hailing to complement public transport in a larger city setting where many journeys are undertaken using a car and where there is a relatively high density of transport infrastructure.

I also found some evidence of an effect on average journey speed among road-based journeys, which can be used as a measure of traffic congestion, but this effect did not prove to be sufficiently robust to be considered causal. Previously, Fageda (2021) found that the presence of ride hailing reduced average congestion in European cities, while Agarwal et al. (2019) found ride hailing increased congestion in Indian cities and Tarduno (2021) found a small increase in congestion in Austin, Texas.

4.1. Policy implications

Overall, the results of my empirical analysis showed that ride hailing had a complementary effect on public transport in Glasgow, and that this specifically affected rail transport. However, while significant, the proportion of total journeys affected by ride hailing appeared to be very small and, therefore, the effect of ride hailing on the overall transport system should not be overstated.

These results indicate that ride hailing can contribute to the move towards sustainable transport. On the basis that ride hailing can help overcome the last-mile problem, the complementarity with public transport could be strengthened by facilitating ride hailing at public transport stations and hubs, for example by ensuring the reliable provision of internet access or facilitating the use of dedicated collection or drop-off spaces alongside registered taxis.

4.2. Limitations and strengths

The findings of this study should be interpreted in the context of certain limitations. First, I had no data on the actual use of ride hailing in Scotland over the study period. My empirical analysis could be improved by a measure of the use of ride hailing in each city, as this would allow an examination of effects by the intensity of ride hailing use. This could also further allay concerns over a possible omitted variable bias that cannot be ruled out as my identification strategy was based purely on temporal variation. Second, although the multinomial logistic regression was a more appropriate model choice than a binary logistic regression, it relied on the assumption of IIA. While the finding of a complementary effect on public transport persisted in a nested logit model that relaxed this assumption, this alternative model involved the use of proxy variables for mode cost and mode quality that were themselves based on several simplifying assumptions. Richer, more granular data on mode characteristics could improve on this approach. Third, it should be highlighted that the use of data from the Scottish Household Survey focused the study on residents of Scotland and their travel behaviour. It is possible that the impact of ride hailing on the travel behaviour of non-residents, such as tourists or people travelling to Scotland in the course of work, is different and this presents an interesting avenue for future research. Fourth, this study centred on Glasgow and Edinburgh, two cities in a developed country. Further research would be required to determine if ride hailing can also have a complementary effect on public transport in a developing city.

Nonetheless, this study can boast several key strengths. First, I employed a difference-in-differences methodology, which allowed me to identify a causal relationship rather than an association between ride hailing and public transport. This approach improved upon many of the studies in this literature that have used cross-sectional data. Second, I drew on travel diary data from a large, representative survey of households in Scotland, the SHS (2020). Several studies in this literature have relied on cross-sectional stated preference surveys of ride hailing users, whereas this travel diary data provided a detailed picture of the journeys made by a representative sample of individuals for each year between 2012 and 2019. This granular data facilitated the difference-in-differences identification strategy using multinomial logistic regressions with a large sample size before and after the introduction of ride hailing, covering cities with and without access to ride hailing. The travel diary data, while still self-reported, provided revealed preference rather than stated preference information, with respondents recording their actual mode choice rather than stating what they would have chosen in a hypothetical scenario. Third, in addition to providing information on mode choice, this travel diary data recorded the purpose of each journey, allowing me to assess heterogeneity in results between work-related and leisure journeys. Furthermore, the travel diary data was also linked to information on the socio-demographic characteristics of survey respondents and their households. This meant that I could control for these characteristics and also analyse heterogeneity in results by demographic and socio-economic status, and thus provide a clearer and more detailed account of the impact of ride hailing on other transport modes.

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Disclosure statement

The author has no competing interests to declare.

CRediT authorship contribution statement

Ciarán Mac Domhnaill: Conceptualisation, Methodology, Software, Formal analysis, Data curation, Writing - original draft, Writing - reviewing and editing, Visualisation.

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Appendix A. Data

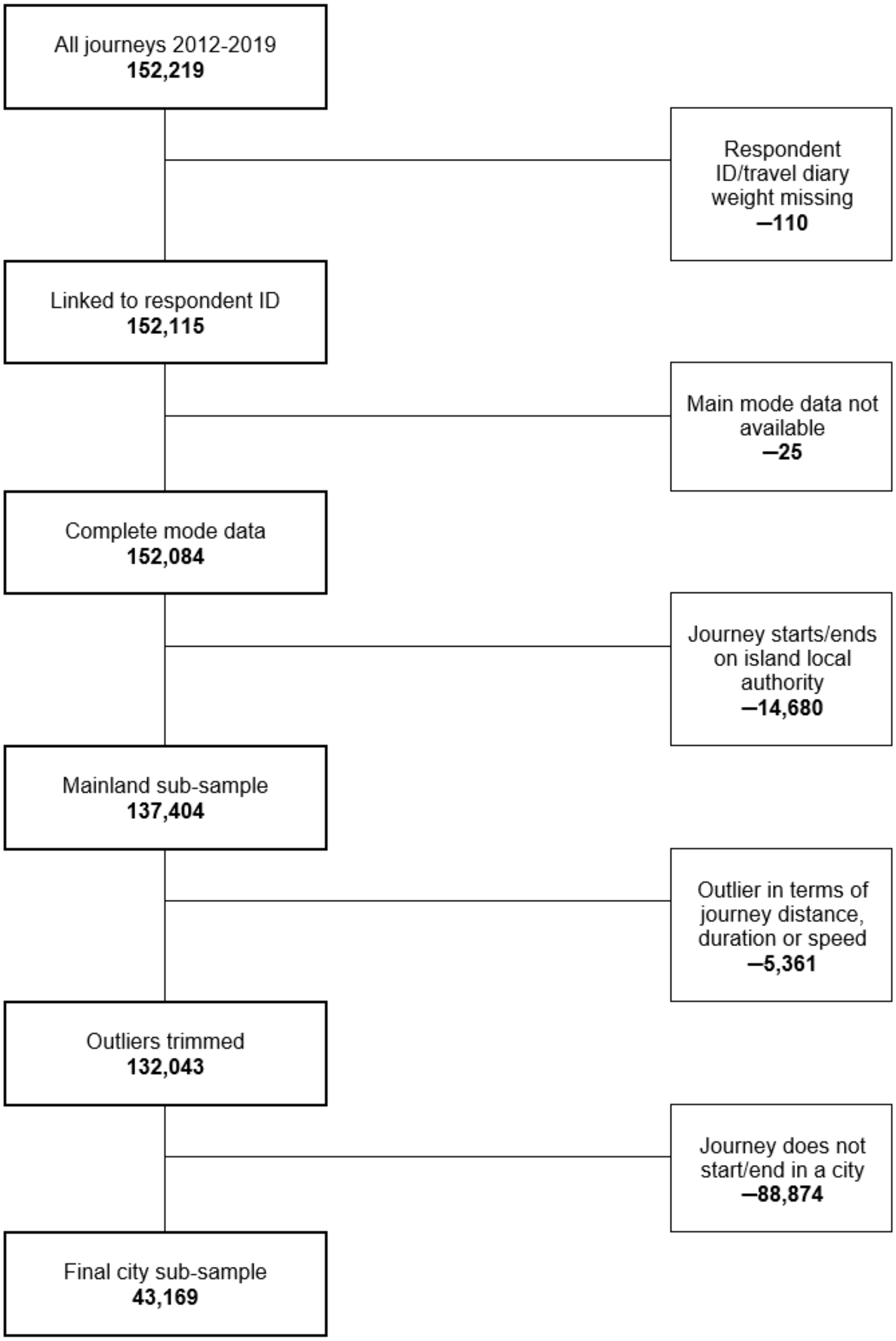


Figure A.11: Flow chart of study sample size from Scottish Household Survey 2012-2019. Sources: Author's analysis; SHS (2020).

Figure A.11 shows how I reduced the sample size of journeys from the SHS (2020), with all journeys recorded in the annual cross sections from 2012 to 2019 combined, to the sample size of 43,169 journeys used for my empirical analysis. First, I removed journeys that were not attached to a respondent ID, and thus could not be matched back to data on respondent characteristics, and journeys for which the travel diary weight or main transport mode (my primary outcome variable) was missing. Second, I removed any that started or ended in the island-based local authority areas of Shetland Islands, Orkney Islands or Na h-Eileanan Siar (the Western Isles) as these would have required air or water transport, which were not the focus of this study. Third, I removed journeys that were outliers in terms of distance, duration or imputed average speed, with outliers defined as being in excess of 3 standard deviations from the mean. Finally, I reduced the remaining Scotland-wide sample to a city sub-sample of journeys that either started or ended in any of the Glasgow City, City of Edinburgh, Dundee City or Aberdeen City local authority areas. The remaining sample of 43,169 journeys, employed throughout my empirical analysis, thus included only mainland journeys that started or ended in the cities of Glasgow, Edinburgh, Dundee or Aberdeen for which data on transport modes and respondent characteristics were available.

Table A.7 details how I collapsed the categorical variable of main transport mode choice available from the SHS (2020) to a five-category variable for my primary outcome variable of interest. Bus and train categories were combined into a public transport category, car/van as passenger and taxi categories were combined into a single category due to the small size of the taxi category, and bicycle was added to the 'other' category due to its small size.

Table A.7: Collapsing categorical variable of mode choice

	Drive	Public	Passenger	Walk	Other	Total
Walking	0	0	0	10431	0	10431
Car/Van as driver	18786	0	0	0	0	18786
Car/Van as passenger	0	0	4694	0	0	4694
Bicycle	0	0	0	0	688	688
Bus	0	5917	0	0	0	5917
Train/Underground	0	1179	0	0	0	1179
Other	0	0	0	0	1139	1139
Taxi/minicab	0	0	335	0	0	335
Total	18786	7096	5029	10431	1827	43169

Drive denotes car as driver
Public denotes public transport
Passenger denotes car as passenger
Bus includes school/work and ordinary service
Other includes motorcycle/moped, ferry, air, horse-riding, tram
Sources: Author's analysis; SHS (2020)

Appendix B. Additional figures and tables

Appendix B.1. Respondent characteristics

I compared the socio-economic and demographic characteristics of the SHS random adults of the control group and each Glasgow (see Table B.8) and Edinburgh (see Table B.9) for 2012-2015, before ride hailing became available. Figures B.12 and B.13 provide graphical illustrations of these characteristics over the entire 2012-2019 study period. Overall, the socio-demographic characteristics of the SHS random adults were broadly similar between the control group and each Glasgow and Edinburgh. Higher levels of education and a higher mean level of total household income were apparent in Edinburgh relative to the control group, while mean household income was lower in Glasgow than in the control group. In addition, a lower proportion of random adults undertaking journeys in Glasgow were married. Time invariant, city-specific socio-demographic factors that may have affected my outcome variables were picked up by city fixed effects γ_c in my regression specifications.

I also employed t-tests to detect differences between 2012 and 2019 in the socio-demographic characteristics of the surveyed random adults for each the Glasgow treatment group (see Table B.10), the Edinburgh treatment group (see Table B.11) and the control group of Dundee and Aberdeen (see Table B.12). These t-tests revealed that the mean of total household income increased in each group over the period. There was also evidence of an increase in education levels in Glasgow and the control group that was not reflected in Edinburgh. The t-tests revealed a 6 per cent increase in the average age among random adults making journeys to or from Edinburgh that was not reflected in Glasgow or the control group. Crucially for the parallel trends assumption of my identification strategy, the linking of these individual-level socio-demographic attributes with the travel diary data allowed me to control for variation in these characteristics in my regression specifications.

Based on these differences, I included 4 individual-level socio-demographic control variables in all regression specifications. These were categorical variables for gender, age group, household education and household income. These were included as categorical variables to account for possible non-linear relationships between these factors and my outcome variables. Figure B.14 displays each of these variables by city.

Table B.8: Socio-demographic characteristics of Glasgow treatment group and control group 2012-2015

	Glasgow	Control	Difference	p-value
Age	47.11	47.53	-0.43	0.36
Female	0.54	0.54	0.01	0.63
Finished school	0.60	0.62	-0.02	0.17
Degree	0.33	0.33	0.00	0.74
Employed	0.59	0.58	0.01	0.56
Retired	0.20	0.22	-0.02	0.11
Married	0.35	0.42	-0.06	0.00
Household income	25495.52	27556.89	-2061.38	0.00
Observations	6069			

Sources: Author's analysis; SHS (2020)

Table B.9: Socio-demographic characteristics of Edinburgh treatment group and control group 2012-2015

	Edinburgh	Control	Difference	p-value
Age	46.81	47.53	-0.72	0.16
Female	0.51	0.54	-0.02	0.11
Finished school	0.73	0.62	0.11	0.00
Degree	0.48	0.33	0.16	0.00
Employed	0.63	0.58	0.05	0.00
Retired	0.21	0.22	-0.01	0.54
Married	0.43	0.42	0.01	0.50
Household income	28743.19	27556.89	1186.29	0.01
Observations	4949			

Sources: Author's analysis; SHS (2020)

Table B.10: Socio-demographic characteristics of Glasgow treatment group in 2012 and 2019

	2019	2012	Difference	p-value
Age	47.62	46.30	1.31	0.10
Female	0.52	0.55	-0.02	0.34
Finished school	0.71	0.59	0.11	0.00
Degree	0.43	0.33	0.10	0.00
Employed	0.62	0.58	0.04	0.11
Retired	0.20	0.21	-0.01	0.63
Married	0.37	0.34	0.03	0.21
Household income	30171.46	25238.15	4933.31	0.00
Observations	1888			

Sources: Author's analysis; SHS (2020)

Appendix B.2. Additional results

To assess the impact of including each of my 4 individual-level variables controlling for socio-demographic characteristics, I first ran my difference-in-differences multinomial logistic regression of mode choice without any control variables, and then proceeded to iteratively add controls to the specification. Column 1 of Table B.13 displays results for the specification

Table B.11: Socio-demographic characteristics of Edinburgh treatment group in 2012 and 2019

	2019	2012	Difference	p-value
Age	48.76	46.01	2.75	0.00
Female	0.56	0.51	0.04	0.11
Finished school	0.70	0.72	-0.02	0.36
Degree	0.43	0.48	-0.05	0.04
Employed	0.63	0.62	0.01	0.61
Retired	0.25	0.21	0.04	0.09
Married	0.40	0.43	-0.02	0.40
Household income	32027.06	27629.91	4397.15	0.00
Observations	1452			

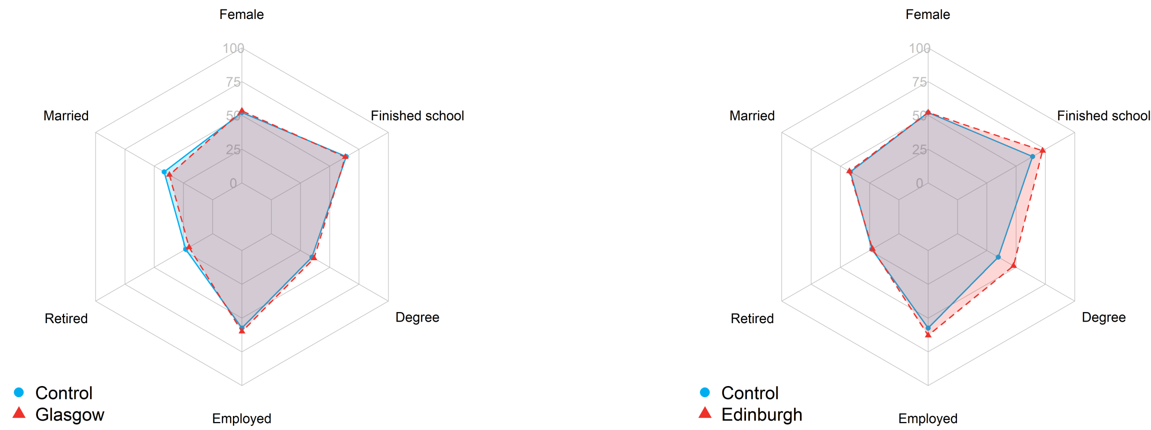
Sources: Author's analysis; SHS (2020)

Table B.12: Socio-demographic characteristics of control group in 2012 and 2019

	2019	2012	Difference	p-value
Age	48.10	47.49	0.61	0.60
Female	0.54	0.56	-0.03	0.43
Finished school	0.69	0.60	0.09	0.00
Degree	0.40	0.31	0.09	0.00
Employed	0.58	0.57	0.01	0.70
Retired	0.23	0.24	-0.01	0.81
Married	0.42	0.42	-0.01	0.85
Household income	31518.12	25892.78	5625.34	0.00
Observations	984			

Control group comprised of Dundee and Aberdeen.
Sources: Author's analysis; SHS (2020)

devoid of control variables. Columns 2 to 5 then iteratively add controls for gender, age, household education and household income. Table B.13 shows that my main result of a positive effect on the use of public transport in Glasgow held across all of these specifications, and that the pseudo-R squared statistic, measuring each regression model's goodness-of-fit (although it should be noted that the pseudo-R squared statistic is not a direct equivalent



(a) Glasgow

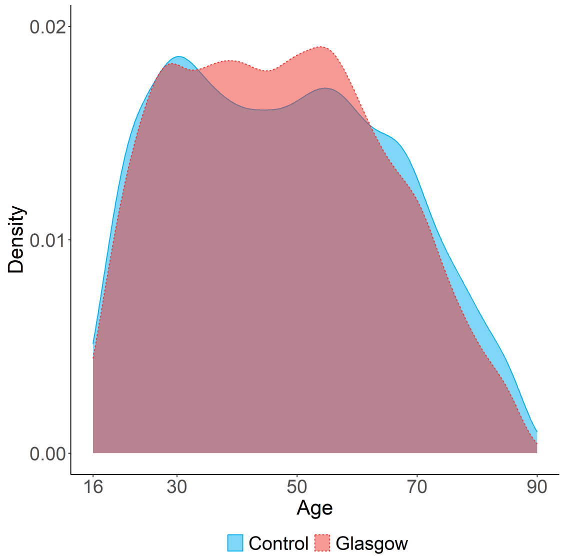
(b) Edinburgh

Figure B.12: Random adult characteristics, control and treatment groups 2012-2019. Control group comprised of Dundee and Aberdeen. Axis shows percentage of random adults. Sources: Author's analysis; SHS (2020).

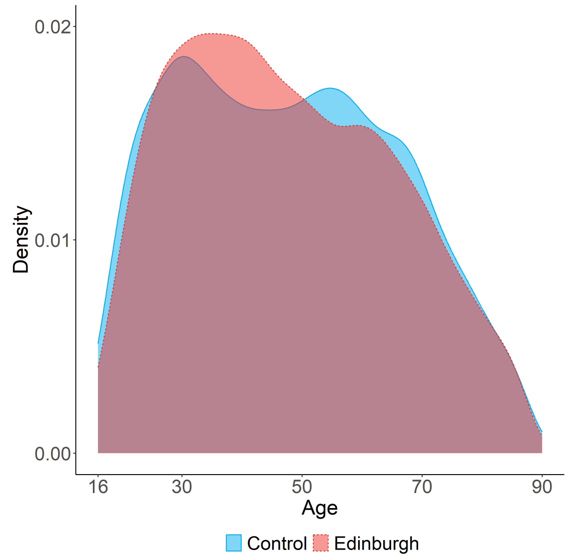
of the R squared statistic from OLS), was improved by the addition of each control variable. Based on this, I proceeded in the rest of my difference-in-differences analysis of mode choice and journey speed including all 4 socio-demographic control variables.

In addition, as shown in Table B.14, I compared various methods for calculating standard errors for my difference-in-differences multinomial logistic regression of mode choice. For assessing the calculation of standard errors, I did not apply travel diary weights to the regression summarised in Table B.14. For ease of comparing standard errors, results are reported as untransformed coefficients and standard errors in Table B.14. Therefore, the regression summarised in Table B.14 corresponds with the regression results shown in column 4 ('unweighted') of Table B.23.

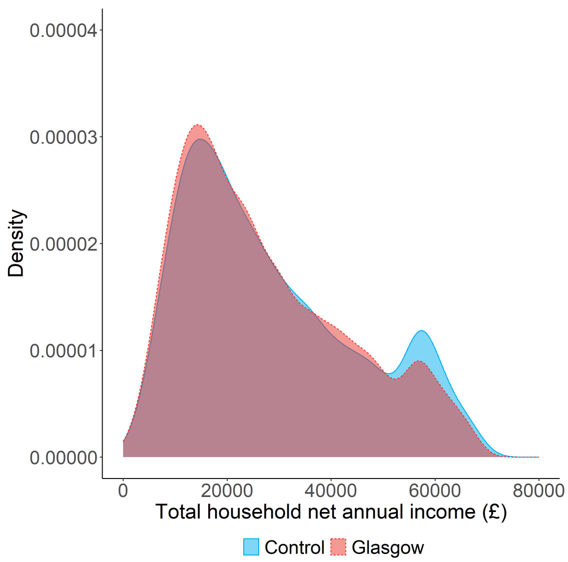
For 'Default' in Table B.14, I calculated standard errors using the default observed information matrix variance estimator, which assumed errors were independent and identically distributed normal. I tested this assumption in 'Robust' by instead using a robust unclus-



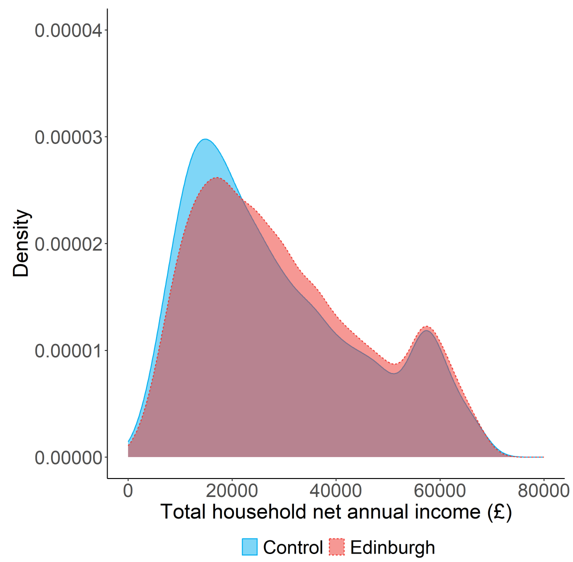
(a) Age, Glasgow



(b) Age, Edinburgh



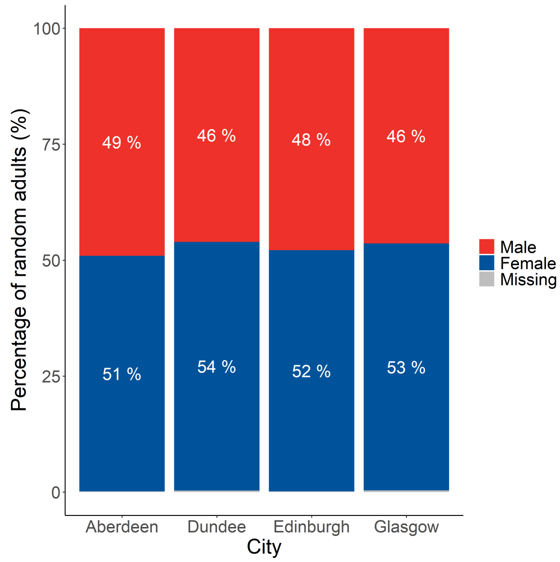
(c) Household income, Glasgow



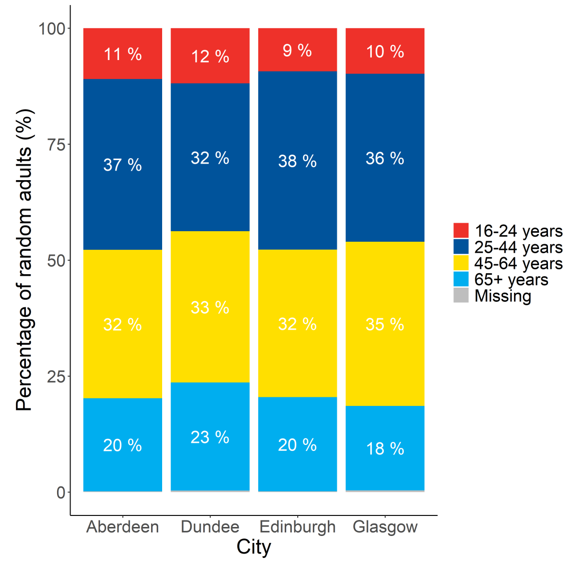
(d) Household income, Edinburgh

Figure B.13: Age and total household net annual income distributions of random adults, control and treatment groups 2012-2019. Control group comprised of Dundee and Aberdeen. Sources: Author's analysis; SHS (2020).

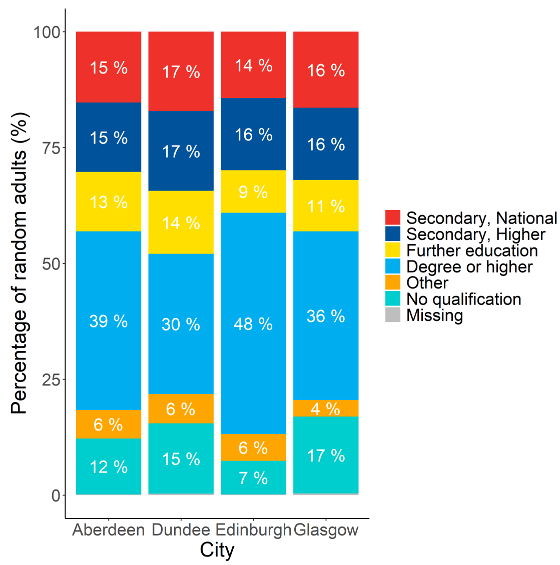
tered Huber/White/sandwich variance estimator (using Stata's vce(robust) option), which allowed for heteroskedasticity, and found little change in standard errors. For 'Clustered', as I discussed in the main paper, I then clustered standard errors at the individual level (using Stata's vce(cluster *cluster variable*) option), which additionally allowed for errors to



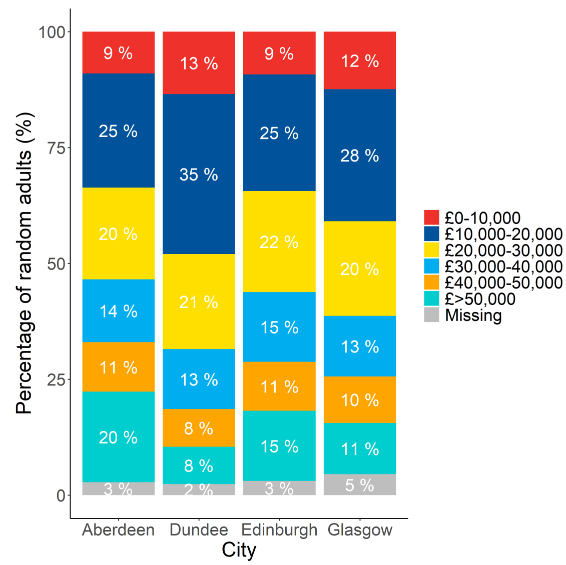
(a) Gender



(b) Age group



(c) Highest education in household



(d) Total household net annual income

Figure B.14: Socio-demographic characteristics of random adults, 2012-2019. Sources: Author's analysis; SHS (2020).

be correlated between journeys recorded by the same individual. This increased standard errors compared with 'Default' and 'Robust', although my main results held. I proceeded in the rest of my econometric analysis of mode choice and journey speed using robust standard errors clustered at the individual level (as in 'Clustered').

Table B.13: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) No controls	(2) Controls	(3) Controls	(4) Controls	(5) Controls
Public					
Treated Glasgow	1.463***	1.461***	1.521***	1.609***	1.749***
	(0.199)	(0.199)	(0.208)	(0.220)	(0.242)
Treated Edinburgh	1.065	1.056	1.089	1.096	1.138
	(0.151)	(0.150)	(0.156)	(0.157)	(0.166)
Passenger					
Treated Glasgow	1.098	1.091	1.143	1.183	1.211
	(0.147)	(0.148)	(0.156)	(0.162)	(0.166)
Treated Edinburgh	1.412**	1.385**	1.428**	1.435**	1.450**
	(0.209)	(0.207)	(0.215)	(0.218)	(0.220)
Walk					
Treated Glasgow	1.204	1.204	1.236*	1.264**	1.381***
	(0.140)	(0.140)	(0.146)	(0.150)	(0.167)
Treated Edinburgh	1.298**	1.295**	1.329**	1.337**	1.385**
	(0.158)	(0.157)	(0.162)	(0.165)	(0.177)
Other					
Treated Glasgow	0.407***	0.409***	0.412***	0.402***	0.424***
	(0.129)	(0.129)	(0.130)	(0.127)	(0.134)
Treated Edinburgh	0.847	0.853	0.856	0.863	0.889
	(0.275)	(0.275)	(0.277)	(0.278)	(0.287)
Observations	43169	43169	43169	43169	43169
Pseudo R^2	0.015	0.023	0.051	0.067	0.091
Year fixed effects	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Control: female	No	Yes	Yes	Yes	Yes
Control: age group	No	No	Yes	Yes	Yes
Control: education	No	No	No	Yes	Yes
Control: income group	No	No	No	No	Yes

Exponentiated coefficients; Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I assessed the sensitivity of my results to the choice of combining Dundee and Aberdeen as the control group by running my main regression of mode choice again using only Dundee journeys, and then using only Aberdeen journeys, as the control group. Results for these

Table B.14: Regression difference-in-differences estimates of ride hailing effect on choice of public transport as main mode in Glasgow

VCE estimator	Coefficient	Standard error	Number of clusters
	0.523		
Default		0.080	-
Robust		0.079	-
Clustered		0.117	16,712
Observations	43169		
Pseudo R^2	0.084		
Year fixed effects	Yes		
City fixed effects	Yes		
Individual controls	Yes		

Sources: Author's analysis; SHS (2020)
VCE denotes variance-covariance matrix of estimator. Standard errors calculated using observed information matrix variance estimator in 'Default'. Robust standard errors calculated using Huber/White/sandwich estimator in 'Robust'. Robust standard errors clustered at individual level in 'Clustered'. Travel diary weights not applied when assessing calculation of standard errors

alternative regressions are summarised (columns 2 and 3 respectively) alongside my main results (column 1) in Table B.15, with the ride hailing effect on the use of public transport in Glasgow holding in both specifications. In addition, to gain confidence in the validity of my key parallel trends assumption, I conducted a placebo test comparing the average change over time in all mainland non-city local authorities with the average change in Dundee and Aberdeen. Reassuringly, as shown in column 4 of Table B.15, no ride hailing effect on mode choice was found in the placebo test.

Table B.16 summarises results for various alternative regression specifications I ran to assess the robustness of my main results. Column 1 repeats my main results for the choice of transport mode. Column 2 shows that these results were largely unchanged by the inclusion of an additional dummy variable in the model that controlled for the opening of Edinburgh Trams. This is a tramway connecting the city centre to Edinburgh airport, which opened to passengers in May 2014. The additional dummy variable was thus set equal to 1 if the journey started or ended in Edinburgh in 2015 or later. The coefficient on the dummy variable was not statistically significant for any comparison transport mode.

I also ran my main regression specification, with mode choice as the outcome variable, again on a sub-sample of journeys that started and ended in the same city, on the basis that ride hailing may be used mainly for short journeys within an urban area. This sub-sample omitted inter-city journeys, and journeys connecting a city with a peripheral local authority. Column 3 of Table B.16 presents summary results for this sub-sample regression, showing that although standard errors were higher due to the smaller sample size, my main results largely continued to hold.

Column 4 of Table B.16 shows summary results for my main regression specification using data that had not been adjusted using any survey weights. These results confirm that my main results were not sensitive to the inclusion of travel diary weights.

Finally, column 5 of Table B.16 summarises results for my alternative regression specification that additionally controlled for city-specific linear trends. I discuss this specification, including its advantages and disadvantages, in the main paper. As expected given the more restrictive regression specification, standard errors were higher (column 5) than in my main results (column 1). As discussed in the paper, these results indicate that the positive effect on public transport in Glasgow did not persist when linear trends were controlled for.

To test whether the effect on public transport affected bus journeys or rail journeys, I ran my main multinomial logistic regression specification again with the mode choice outcome variable amended to split the public transport category into separate bus and rail categories. Results for this regression are displayed alongside my repeated main results in Table B.17, with bus and rail categories separated in column 2. These results clearly indicate that the public transport effect stemmed from rail journeys, with significant positive effects found on the use of rail in both Glasgow and Edinburgh. Meanwhile, no effect was found among bus journeys in either city.

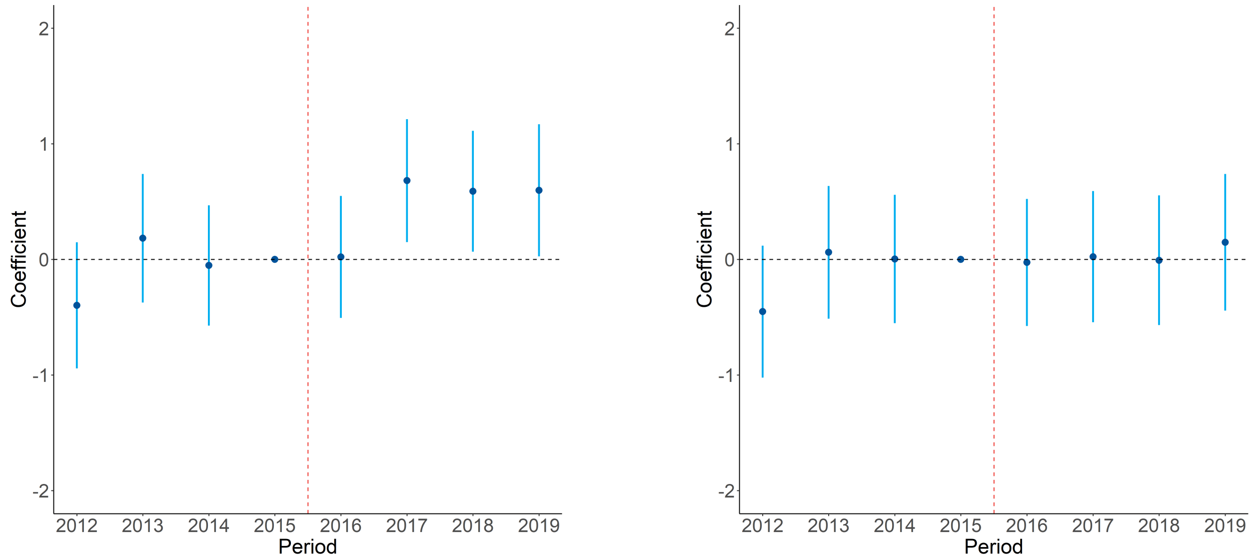
To test the difference in the proportion of public transport journeys that also involved taking a car as a passenger before and after the introduction of ride hailing, I ran a logistic regression of this proportion on a $POST_t$ dummy that was equal to 1 if the journey occurred in 2016 or later, and 0 otherwise. As reported in Table B.18, I found a significant increase in the probability that a public transport journey also involved the use of a car as a passenger in the period after the launch of ride hailing.

Appendix B.3. Untransformed multinomial logistic regression coefficients

In the paper, for greater ease of interpretation, I report multinomial logistic regression results as exponentiated coefficients, or relative risk ratios. For those more partial to interpreting results from untransformed coefficients, Tables B.19, B.20, B.21, B.22, B.23 and B.24, and Figure B.15 present these same multinomial logistic regression results as raw coefficients with corresponding untransformed standard errors. These coefficients show the change in the multinomial log-odds of the respective mode being chosen over the reference transport mode (driving a car) due to ride hailing becoming available in that city.

Appendix B.4. Nested logit regression results

My main regression specification was a multinomial logistic regression, which imposed the assumption of independence of irrelevant alternatives (IIA). I also ran a nested logistic regression to relax this assumption and allow for modes that may be affected by the same random shocks to be grouped together. This involved separating the mode choice decision into different 'levels', summarised in the 'tree' structure shown in Figure B.16. For the bottom-level alternatives in this nested logit, I disaggregated public transport into bus and rail and disaggregated bicycle from the 'other' category, giving 7 alternative modes: car as driver, car as passenger, bus, rail, walk, bicycle, other. I could then specify an upper level of 5 alternative mode 'types': car as driver, car as passenger, public transport, active travel, other. This specification allowed some random shocks to affect an individual's decision to choose each mode independently (for example rail), and other random shocks to affect the type of



(a) Glasgow

(b) Edinburgh

Figure B.15: Regression difference-in-differences estimates coefficients and 95 per cent confidence intervals for effect of ride hailing effect on public transport, generalised model 2012-2019. Robust standard errors clustered at individual level. Uber operating in Glasgow and Edinburgh from 2016 onwards (red dashed line). Sources: Author's analysis; SHS (2020).

mode chosen (for example public transport). The structure of this tree (shown in Figure B.16) is set by the researcher. While I also tested other plausible tree structures, these other models achieved dissimilarity parameters of greater than 1, leading to the rejection of those models. This regression was estimated using maximum likelihood and a parametrisation consistent with a random utility model. As with my multinomial logistic regressions, I set car as driver as the reference mode.

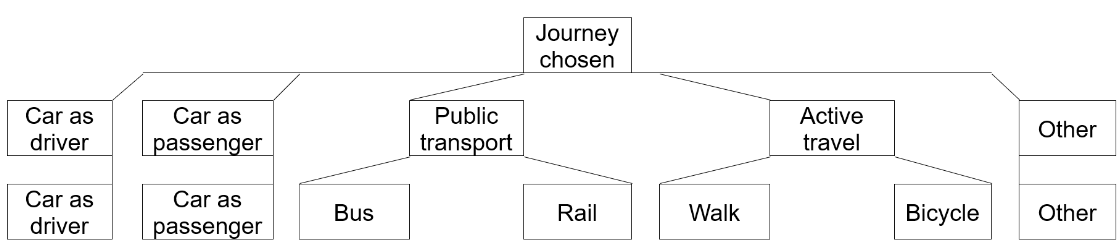


Figure B.16: Tree structure specified for nested logit regression model

My multinomial logistic regression analysis involved individual-specific control variables in addition to the difference-in-differences structure. In the nested logit model, I applied these individual controls and difference-in-differences variables to the upper decision level, choosing between mode types. Additional, mode-specific variables were required for the bottom-level decision, choosing between modes. Ideally, these variables would capture mode attributes such as cost and quality. For this purpose, I generated 2 mode-specific proxy variables for mode cost and speed.

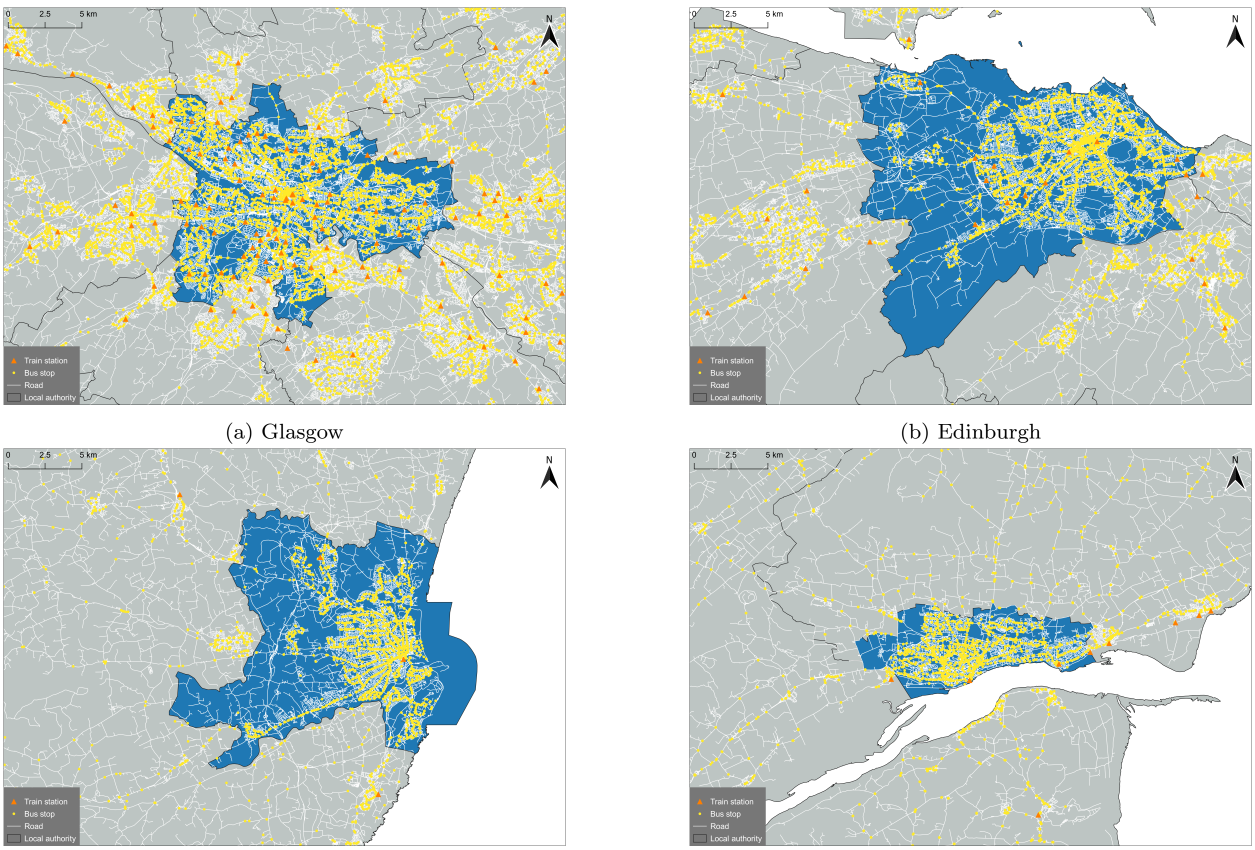
Mode cost. For car as driver and car as passenger, I employed a UK-wide index of typical retail petrol prices in pence per litre (see Appendix C for details), and multiplied this by journey distance for each journey in the sample assuming a constant fuel efficiency level of 7.5 litres of petrol per 100km over the 2012-2019 study period. For public transport, I took the current bus and rail fares for within-city journeys in 2024 (based on an online search of operator websites and displayed in Table B.25), and applied these to fare price indices (see Appendix C for details) to create city-specific time series for bus and rail fares. I assumed walk, bicycle and 'other' cost nothing. The calculation of these figures required several simplifying assumptions, and this mode cost variable could only be regarded as a proxy for mode cost.

Mode speed. For each city-year-mode combination, I calculated the mean of average journey speeds among my sample of 43,169 journeys as an approximate measure of the speed of transport modes. For example, this would capture the fact that the same journey would generally take longer to walk than to drive. Of course, to some extent, these figures were endogenous in the decision model and this variable could only be interpreted as a rough proxy for mode quality in terms of journey time.

Table B.26 reports results for this alternative econometric specification, indicating that my result of a complementary effect on public transport was found in both Glasgow and Edinburgh, with a larger effect found in Glasgow. The dissimilarity parameters associated with this specification, reported in Table B.27, all lie between 0 and 1 as required for consistency with principles of random utility maximisation.

Appendix C. Transport in Scotland

Across the UK, the provision of public transport has been characterised by privatisation for some time. Bus services were privatised from 1986, and this was followed by the privatisation of railways in 1993.[7] In Scotland, all commuter rail services are operated by ScotRail, a brand name that has been owned by various private companies but was re-nationalised by the Scottish Government in 2022. Local bus services in Scotland are provided by private operators.



(a) Glasgow

(b) Edinburgh

(c) Aberdeen

(d) Dundee

Figure C.17: Roads and public transport stops, 2020. Source: Author's analysis; UK Department for Transport (2020a); Ordnance Survey (2020).

[7] See Gunn (2018) for a history of transport systems in the UK.

Appendix C.1. City transport profiles

Figure 3 in the main paper maps the geographical locations of Glasgow, Edinburgh, Aberdeen and Dundee within Scotland. Figure C.17 illustrates the road networks, bus stops and railway stations in each of the 4 cities as of 2020.

Glasgow has an international airport, and the city is served by an extensive road network, suburban railway lines and a light metro line. Several motorways run through the city, including the M8 connecting with Edinburgh to the east, the M73, the M74 connecting with England to the south, the M77 and the M80.[8] A low emission zone (LEZ), where all vehicles that do not meet a low-emissions standard are charged a penalty fee, has applied to bus vehicles in central Glasgow since 2018, and to other vehicles since June 2023 (although residents of the LEZ are exempt until 2024). Glasgow's suburban railway is operated by ScotRail and based around the Glasgow Central and Glasgow Queen Street terminus stations. Several private operators provide an extensive bus network in the city. A single circular light metro route, Glasgow Subway, has been in operation since 1896 and was modernised in 1977. There has been no tram network in Glasgow since 1962.

Edinburgh is also served by an international airport, in addition to road and rail networks. The Edinburgh City Bypass (A720) links with major roads including the M8 connecting with Glasgow to the west, the A1 connecting with England to the south, and the M9. There are currently no congestion charges in the city, although a LEZ will be enforced from 2024. The suburban railway is operated by ScotRail and based in the terminus station of Edinburgh Waverley. The main public transport option in Edinburgh is the bus network, which is operated by private companies. Edinburgh's original tram system closed in 1956, but Edinburgh Trams, a single route connecting the airport on the western outskirts of the city to Prince's Street and St Andrews Square in the city centre, was opened in May 2014.

[8]In the UK, motorway numbers are prefixed with 'M'. There is also a network of major non-motorway roads that are numbered with the prefix 'A', known as A-roads.

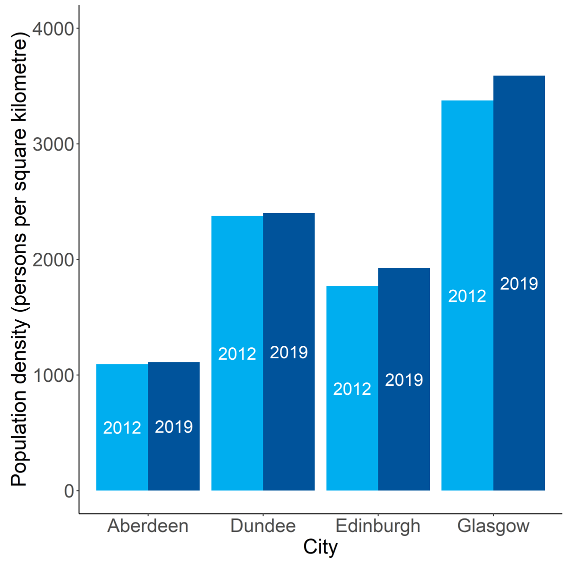
Aberdeen has a small international airport and also boasts a major helicopter terminal that serves offshore oil installations in the North Sea. A network of 6 A-roads connects the city with the rest of Scotland. There are currently no congestion charges in the city, although a LEZ will be enforced from 2024. ScotRail operates the suburban railway, with 2 railway stations in the city. There is also a bus network in the city, offered by private operators. There has been no tram network in Aberdeen since 1958.

There is a small domestic airport in **Dundee**, and the city is served by the A90 road that connects with Aberdeen to the north and to the M90 motorway. There are currently no congestion charges in the city, although a LEZ will be enforced from 2024. As with Aberdeen, there are 2 main railway stations in the city and the suburban railway is operated by ScotRail. Similar to the other three cities, Dundee's tram system was closed in 1956 with routes replaced by diesel buses, and the city now has an extensive bus network operated by private companies.

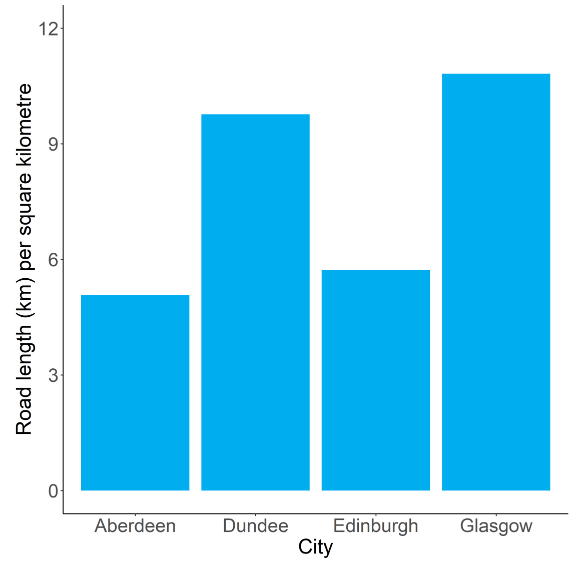
While statistics on population density or the density of transport infrastructure are partly determined by the boundaries of the city administrative areas, it can be observed from Figure C.17 that infrastructure density is higher in Glasgow than in other cities. To emphasise this, Figure C.18 compares population and infrastructure density across the 4 cities, with Glasgow boasting the highest density in terms of population, roads, bus stops and particularly rail stations. While both Glasgow and Edinburgh are larger population centres than Dundee and Aberdeen, as shown in Figure 2 in the main paper, Glasgow is a denser city than Edinburgh, and in particular is served by a more extensive rail network. This may offer some explanation for a difference in treatment effects between these cities.

Appendix C.2. Changes in transport infrastructure

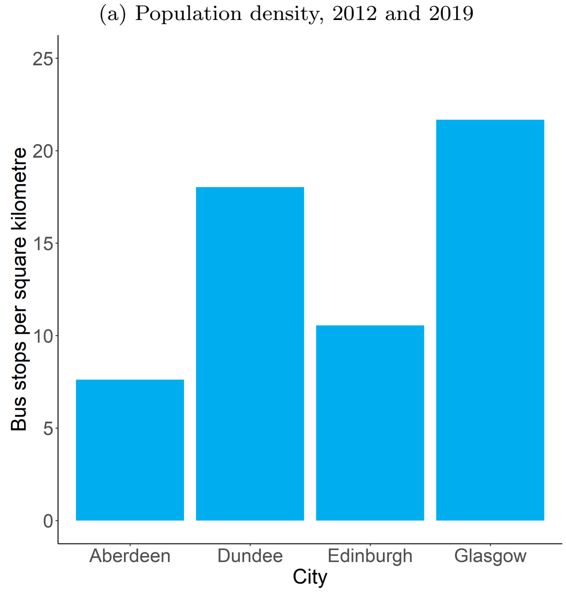
Figure C.19 displays some statistics on changes in transport infrastructure in Scotland during my study period between 2012 and 2019. First, there was very little change in the



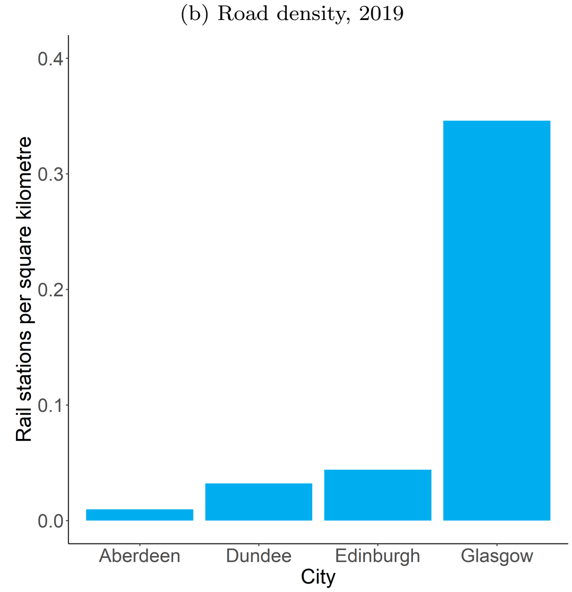
(a) Population density, 2012 and 2019



(b) Road density, 2019



(c) Bus stop density, 2020



(d) Rail station density, 2020

Figure C.18: Population density and density of transport infrastructure by city. Source: Author's analysis; Office for National Statistics (2020); Ordnance Survey (2020); UK Department for Transport (2020a,b).

total length of the road network in any of the 4 cities, ranging from a 5.82 per cent increase in Aberdeen to a 2.68 per cent increase in Dundee between 2012 and 2019. Any effect on my outcome variables from this small increase in road length across all 4 cities would be captured by the year fixed effects, while the fact that total road length is different between cities would be captured by the city fixed effects.

Second, there was virtually no change in the number of passenger rail stations across the 4 cities between 2012 and 2019. One new station, Edinburgh Gateway, opened in Edinburgh in 2016 to provide a connection with Edinburgh Trams near the airport.

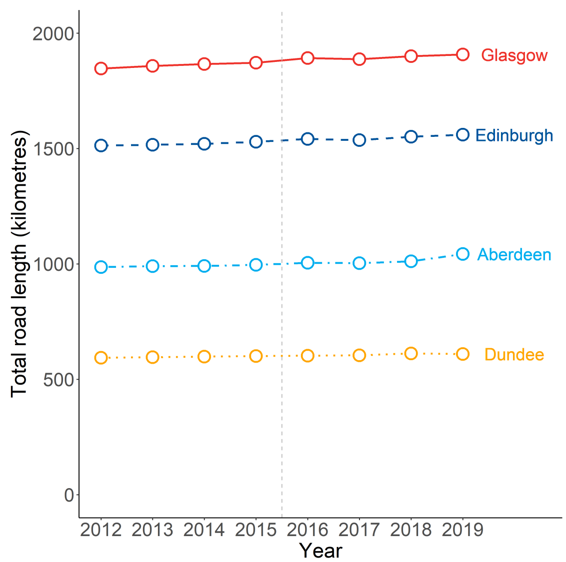
Third, there was more change evident in the number of licensed bus vehicles. While there was little change in Aberdeen or Dundee, Glasgow experienced a 15 per cent decline in licensed bus vehicles in 2017 before recovering slightly in 2019, while there was a steady increase of 35.37 per cent between 2012 and 2019 in Edinburgh.

Fourth, the number of licensed taxi vehicles was almost static between 2012 and 2019 in both Glasgow and Edinburgh. However, the number of taxis was 17.35 per cent lower in Aberdeen, and 11.53 per cent lower in Dundee, in 2019 than in 2012.

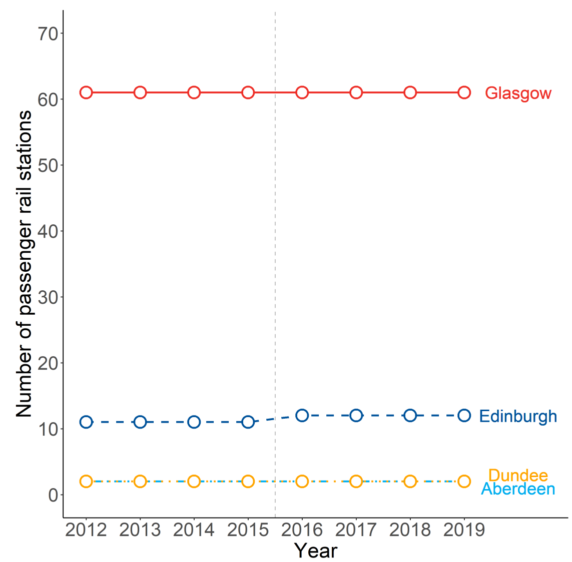
Appendix C.3. Changes in transport prices

While the extent of transport infrastructure may not have changed substantially between 2012 and 2019, Figure C.20 paints a different picture for transport prices, namely road fuel prices and public transport fares. However, while there was no city-level data available for these variables, I argue here that there are unlikely to have been significant city-specific changes during this time.

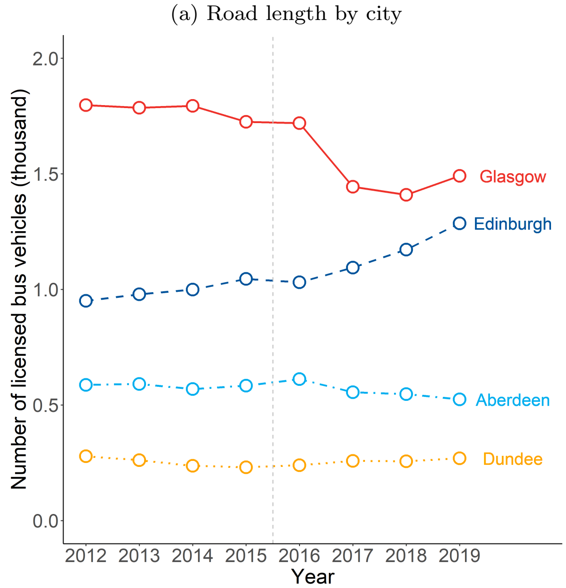
First, local bus fares in Scotland increased by 26.14 per cent over the course of my study period, compared with 21.05 per cent more broadly in Great Britain. Figure C.20 shows that the increase in local bus fares was closely related to the increase in the retail price index for Great Britain. There was a similar increase of 17.92 per cent in rail fares across Great Britain. Any effect on my outcome variables of this general increase in public transport fares, which appears to have been largely in line with inflation in retail prices, would have been captured by the year fixed effects, while the city fixed effects would have accounted for any city-specific differences that did not change over time. The possibility of city-specific changes



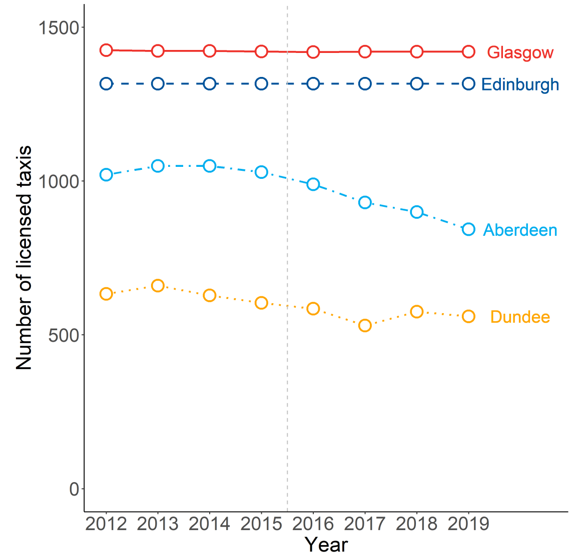
(a) Road length by city



(b) Number of passenger rail stations by city



(c) Number of licensed bus vehicles by city



(d) Number of licensed taxi vehicles by city

Figure C.19: Transport infrastructure in Scotland, 2012-2019. Ride hailing became available in Glasgow and Edinburgh in late 2015 (grey dashed line). Source: Author's analysis; Transport Scotland (2020); UK Department for Transport (2020b).

over time in public transport fares between 2012 and 2019 seems remote, particularly in the case of rail transport since ScotRail is the single operator for the suburban rail network across all 4 cities.

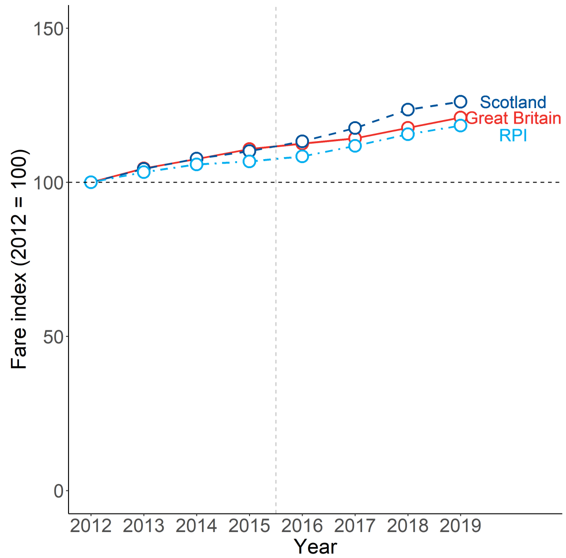
Second, there was considerable fluctuation in fuel prices between 2012 and 2019 in the

UK. Figure C.20 indicates very similar patterns in typical retail prices for premium unleaded petrol and diesel, with a significant decrease during 2014 and 2015 before a subsequent steady recovery for the prices of both fuels. Figure C.20 also plots the price index for crude oil acquired by refineries over this period, as I contend that these changes in road fuel prices were mainly influenced by the price of crude oil, a factor exogenous to transport systems in Scotland. In addition, taxes on road fuel are applied at a UK level and thus would not vary between cities. Any effect on my outcome variables from city-specific deviations in fuel prices from these UK-wide typical retail prices, that could arise from other factors such as fuel transport or storage costs, would have been captured by the city fixed effects unless these city-specific differences changed significantly over time between 2012 and 2019, which seems unlikely.

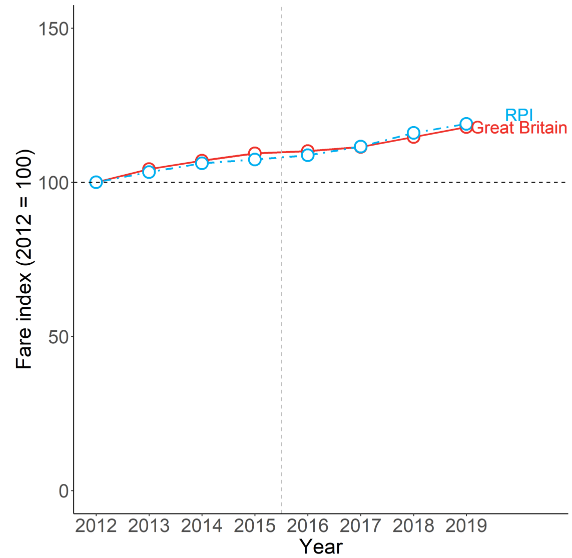
Appendix C.4. Changes in aggregate transport use

While this study focused on individual journeys using SHS (2020) travel diary data, it is also worth looking at aggregate measures of transport use. In my study setting of Glasgow, Edinburgh, Dundee and Aberdeen between 2012 and 2019, such aggregate data did not afford large enough sample sizes to apply the difference-in-differences methodology employed with travel diary data. However, Figures C.21 and C.22 offer some descriptive statistics of these aggregate measures.

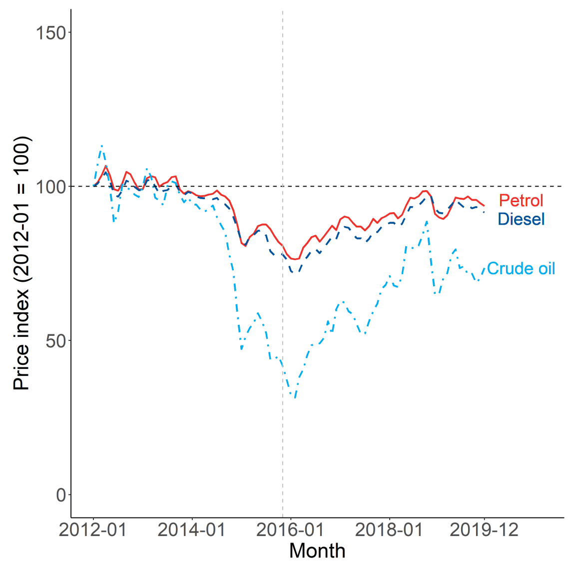
Figure C.21 displays annual aggregate statistics on private car ownership, car traffic and road traffic collisions by city. The number of licensed private cars increased steadily by 10.16 per cent in Edinburgh, 3.73 per cent in Aberdeen and 12.74 per cent in Dundee between 2012 and 2019. A sharp decrease in licensed cars of 14.07 per cent was evident in Glasgow in 2017, the same year in which I first found a significant positive effect of ride hailing on public transport. Despite this, however, there was relatively little change during the study period in total car traffic (measured in vehicle kilometres) across the 4 cities, apart from a



(a) Index of local bus fares, Scotland and Great Britain 2012-2019 (2012 = 100). 'RPI' shows retail price index for Great Britain.



(b) Index of rail fares (all ticket types), Great Britain 2012-2019 (2012 = 100). 'RPI' shows retail price index for Great Britain.

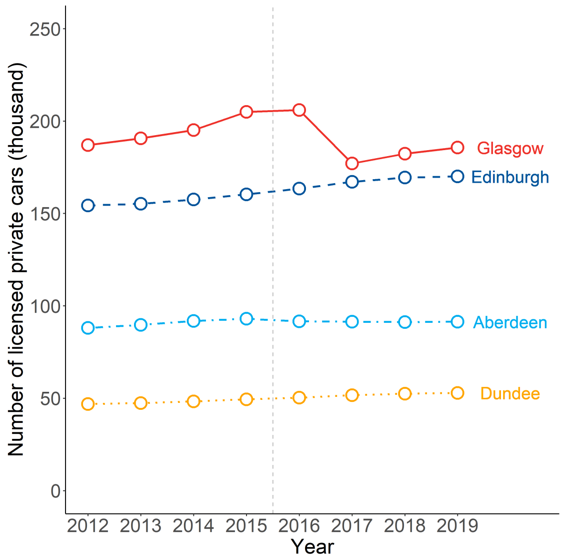


(c) Indices of typical retail prices for petrol (premium unleaded) and diesel, UK 2012-2019 (January 2012 = 100). 'Crude oil' shows price index for crude oil acquired by refineries.

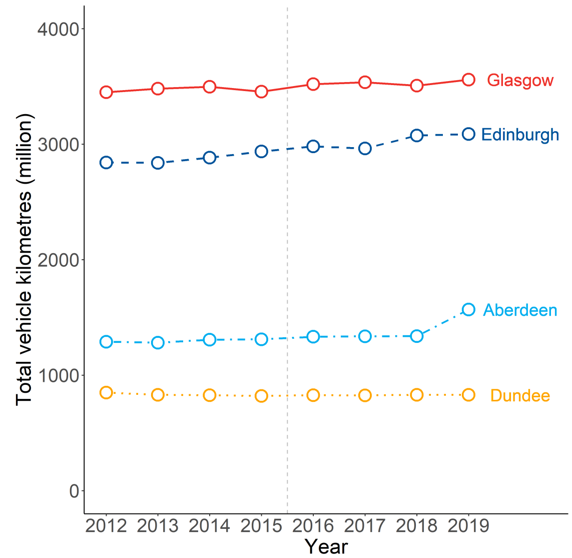
Figure C.20: Transport prices in the UK, 2012-2019. Ride hailing became available in Glasgow and Edinburgh in late 2015 (grey dashed line). Source: Author's analysis; UK Department for Energy Security and Net Zero (2023b); UK Department for Transport (2023); Office of Rail and Road (2022).

notable increase in Aberdeen in 2019. The number of road traffic collisions declined over the study period, with particularly pronounced declines of 33.78 per cent and 36.31 per cent in

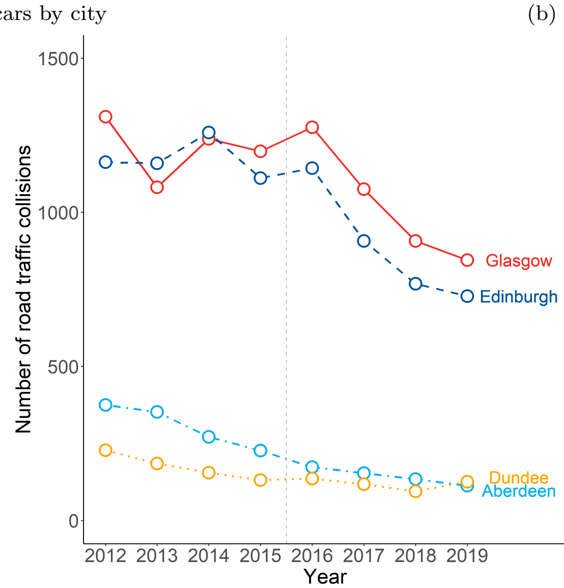
Glasgow and Edinburgh respectively between 2016 and 2019. Consistent with my difference-in-differences results using SHS (2020) travel diary data, there is no evidence in Figure C.21 of a substantial increase in car use in Glasgow or Edinburgh following the introduction of ride hailing in late 2015.



(a) Licensed private cars by city



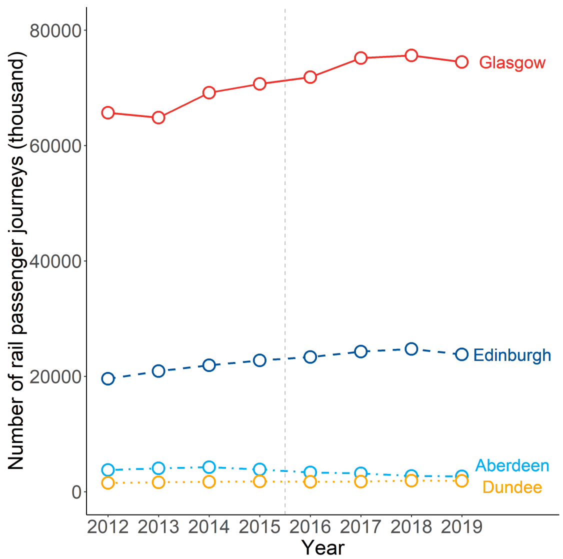
(b) Car traffic by city



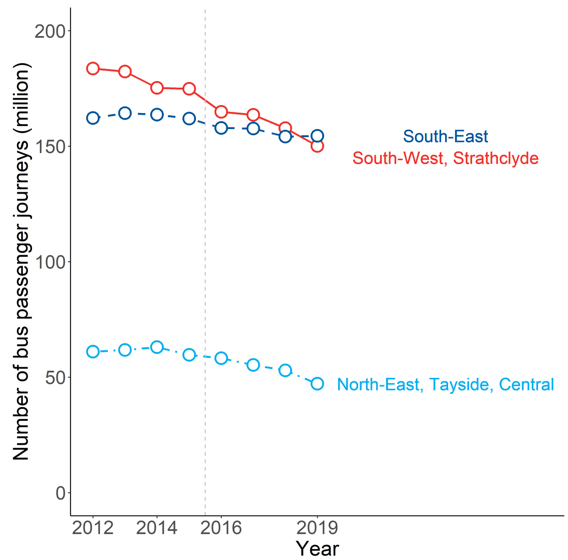
(c) Number of road traffic collisions by city

Figure C.21: Aggregate measures of car use by city or region, 2012-2019. Ride hailing became available in Glasgow and Edinburgh in late 2015 (grey dashed line). Source: Author's analysis; UK Department for Transport (2022); Transport Scotland (2020).

Figure C.22, meanwhile, depicts annual aggregate statistics on public transport use during the study period. Between 2012 and 2019, the number of within-Scotland rail passenger journeys (measured by origin or destination city) increased by 13.42 per cent, 21.51 per cent and 23.8 per cent in Glasgow, Edinburgh and Dundee respectively, while journeys actually decreased by 29.8 per cent in Aberdeen. There was a 4.64 per cent increase in rail passenger journeys to or from Glasgow in 2017 alone, reflective of my difference-in-differences results for Glasgow. On the other hand, the number of local bus journeys was decreasing across Scotland over this period, with a decrease of 18.25 per cent in the South-West and Strathclyde region (including Glasgow), 4.73 per cent in the South-East region (including Edinburgh), and 22.8 per cent in the North-East, Tayside and Central region (including Dundee and Aberdeen) between 2012 and 2019. The substantial decrease in the South-West region is reflective of the decline in the number of licensed bus vehicles in Glasgow, while the much smaller decrease in journeys in the South-East region may be linked to the increase in bus vehicles in Edinburgh (see Figure C.19).



(a) Number of within-Scotland passenger rail journeys by origin or destination city



(b) Number of bus passenger journeys by region. Glasgow is in South-West, Strathclyde; Edinburgh is in South-East; Dundee and Aberdeen are both in North-East, Tayside, Central.

Figure C.22: Aggregate measures of public transport use by city or region, 2012-2019. Ride hailing became available in Glasgow and Edinburgh in late 2015 (grey dashed line). Source: Author's analysis; Transport Scotland (2020).

Table B.15: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) Main	(2) Dundee	(3) Aberdeen	(4) Placebo
Public				
Treated Glasgow	1.749***	1.810***	1.685***	
	(0.242)	(0.325)	(0.300)	
Treated Edinburgh	1.138	1.189	1.097	
	(0.166)	(0.220)	(0.202)	
Placebo treatment				0.960
				(0.128)
Passenger				
Treated Glasgow	1.211	1.024	1.397**	
	(0.166)	(0.182)	(0.238)	
Treated Edinburgh	1.450**	1.234	1.669***	
	(0.220)	(0.234)	(0.304)	
Placebo treatment				1.038
				(0.120)
Walk				
Treated Glasgow	1.381***	1.381**	1.366**	
	(0.167)	(0.215)	(0.205)	
Treated Edinburgh	1.385**	1.396**	1.372**	
	(0.177)	(0.225)	(0.213)	
Placebo treatment				1.070
				(0.102)
Other				
Treated Glasgow	0.424***	0.741	0.257***	
	(0.134)	(0.346)	(0.099)	
Treated Edinburgh	0.889	1.562	0.534	
	(0.287)	(0.735)	(0.209)	
Placebo treatment				0.762
				(0.236)
Observations	43169	37350	37930	99932
Pseudo R^2	0.091	0.086	0.088	0.076
Year fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes

Exponentiated coefficients; Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Control group consist of only Dundee in Column 2
Control group consists of only Aberdeen in Column 3
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.16: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) Main	(2) Tram	(3) Within-city	(4) Unweighted	(5) Linear trend
Public					
Treated Glasgow	1.749***	1.754***	1.729***	1.687***	1.077
	(0.242)	(0.243)	(0.295)	(0.198)	(0.308)
Treated Edinburgh	1.138	1.054	1.042	1.145	0.799
	(0.166)	(0.173)	(0.176)	(0.141)	(0.243)
Passenger					
Treated Glasgow	1.211	1.214	1.515**	1.224*	0.562**
	(0.166)	(0.167)	(0.279)	(0.144)	(0.154)
Treated Edinburgh	1.450**	1.358*	1.355	1.331**	1.225
	(0.220)	(0.249)	(0.256)	(0.170)	(0.390)
Walk					
Treated Glasgow	1.381***	1.384***	1.480***	1.393***	1.181
	(0.167)	(0.168)	(0.211)	(0.145)	(0.292)
Treated Edinburgh	1.385**	1.274*	1.360**	1.359***	1.196
	(0.177)	(0.187)	(0.193)	(0.148)	(0.310)
Other					
Treated Glasgow	0.424***	0.424***	0.381**	0.351***	1.406
	(0.134)	(0.134)	(0.154)	(0.095)	(0.731)
Treated Edinburgh	0.889	0.853	0.804	0.831	1.131
	(0.287)	(0.296)	(0.326)	(0.234)	(0.581)
Observations	43169	43169	28328	43169	43169
Pseudo R^2	0.091	0.091	0.084	0.084	0.092
Year fixed effects	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes
Edinburgh tram control	No	Yes	No	No	No
Travel diary weights	Yes	Yes	Yes	No	Yes
Linear trend	No	No	No	No	Yes

Exponentiated coefficients; Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.17: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) Main	(2) Rail
Public		
Treated Glasgow	1.749***	
	(0.242)	
Treated Edinburgh	1.138	
	(0.166)	
Passenger		
Treated Glasgow	1.211	1.190
	(0.166)	(0.163)
Treated Edinburgh	1.450**	1.444**
	(0.220)	(0.220)
Walk		
Treated Glasgow	1.381***	1.341**
	(0.167)	(0.162)
Treated Edinburgh	1.385**	1.378**
	(0.177)	(0.176)
Other		
Treated Glasgow	0.424***	0.455**
	(0.134)	(0.142)
Treated Edinburgh	0.889	0.968
	(0.287)	(0.311)
Bus		
Treated Glasgow		1.142
		(0.168)
Treated Edinburgh		1.048
		(0.159)
Rail		
Treated Glasgow		6.205***
		(2.464)
Treated Edinburgh		2.372**
		(1.019)
Observations	43169	43057
Pseudo R^2	0.091	0.098
Year fixed effects	Yes	Yes
City fixed effects	Yes	Yes
Individual controls	Yes	Yes

Exponentiated coefficients; Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.18: Post-treatment coefficient for use of car as passenger as part of journey

	(1)
Car as passenger used in stage	
POST	13.368^{***}
	(8.664)
Observations	6017
Pseudo R^2	0.210
Individual controls	Yes

Exponentiated coefficients; Standard errors in parentheses
Standard errors clustered at individual level
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.19: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) Main	(2) Under 45	(3) Male	(4) Employed	(5) High income	(6) Degree
Public						
Treated Glasgow	0.559***	0.641***	0.839***	0.729***	1.094***	0.592**
	(0.139)	(0.209)	(0.210)	(0.189)	(0.322)	(0.257)
Treated Edinburgh	0.129	0.014	0.252	0.292	0.330	0.123
	(0.146)	(0.218)	(0.215)	(0.193)	(0.321)	(0.254)
Passenger						
Treated Glasgow	0.191	0.032	-0.060	0.189	0.324	-0.020
	(0.137)	(0.202)	(0.227)	(0.187)	(0.276)	(0.226)
Treated Edinburgh	0.372**	0.150	0.415	0.247	0.463	0.240
	(0.152)	(0.227)	(0.257)	(0.208)	(0.302)	(0.248)
Walk						
Treated Glasgow	0.323***	0.272	0.213	0.289*	0.538**	0.071
	(0.121)	(0.170)	(0.173)	(0.160)	(0.264)	(0.192)
Treated Edinburgh	0.325**	0.177	0.285	0.244	0.321	0.253
	(0.128)	(0.180)	(0.183)	(0.159)	(0.262)	(0.184)
Other						
Treated Glasgow	-0.859***	-0.494	-0.287	-0.880**	-0.390	-1.215***
	(0.316)	(0.382)	(0.375)	(0.385)	(0.745)	(0.454)
Treated Edinburgh	-0.118	0.048	0.231	-0.251	0.293	-0.154
	(0.323)	(0.394)	(0.386)	(0.392)	(0.745)	(0.458)
Observations	43169	20290	19978	25805	10333	17758
Pseudo R^2	0.091	0.089	0.100	0.067	0.071	0.071
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.20: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) Main	(2) Work	(3) Leisure
Public			
Treated Glasgow	0.559***	1.019***	0.327
	(0.139)	(0.237)	(0.285)
Treated Edinburgh	0.129	0.646***	-0.255
	(0.146)	(0.242)	(0.289)
Passenger			
Treated Glasgow	0.191	-0.032	0.450*
	(0.137)	(0.333)	(0.234)
Treated Edinburgh	0.372**	-0.009	0.583**
	(0.152)	(0.387)	(0.255)
Walk			
Treated Glasgow	0.323***	0.117	0.501**
	(0.121)	(0.246)	(0.234)
Treated Edinburgh	0.325**	0.251	0.116
	(0.128)	(0.237)	(0.240)
Other			
Treated Glasgow	-0.859***	-0.786*	-1.328**
	(0.316)	(0.463)	(0.538)
Treated Edinburgh	-0.118	0.007	-0.925*
	(0.323)	(0.470)	(0.560)
Observations	43169	11224	8526
Pseudo R^2	0.091	0.094	0.098
Year fixed effects	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes

Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.21: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) No controls	(2) Controls	(3) Controls	(4) Controls	(5) Controls
Public					
Treated Glasgow	0.381***	0.379***	0.419***	0.476***	0.559***
	(0.136)	(0.136)	(0.137)	(0.137)	(0.139)
Treated Edinburgh	0.063	0.054	0.085	0.092	0.129
	(0.142)	(0.142)	(0.143)	(0.143)	(0.146)
Passenger					
Treated Glasgow	0.093	0.087	0.134	0.168	0.191
	(0.134)	(0.136)	(0.136)	(0.137)	(0.137)
Treated Edinburgh	0.345**	0.325**	0.356**	0.361**	0.372**
	(0.148)	(0.150)	(0.151)	(0.152)	(0.152)
Walk					
Treated Glasgow	0.185	0.185	0.212*	0.234**	0.323***
	(0.117)	(0.116)	(0.118)	(0.119)	(0.121)
Treated Edinburgh	0.261**	0.259**	0.284**	0.290**	0.325**
	(0.121)	(0.121)	(0.122)	(0.123)	(0.128)
Other					
Treated Glasgow	-0.900***	-0.895***	-0.888***	-0.912***	-0.859***
	(0.317)	(0.316)	(0.316)	(0.316)	(0.316)
Treated Edinburgh	-0.166	-0.159	-0.155	-0.147	-0.118
	(0.324)	(0.322)	(0.323)	(0.322)	(0.323)
Observations	43169	43169	43169	43169	43169
Pseudo R^2	0.015	0.023	0.051	0.067	0.091
Year fixed effects	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Control: female	No	Yes	Yes	Yes	Yes
Control: age group	No	No	Yes	Yes	Yes
Control: education	No	No	No	Yes	Yes
Control: income group	No	No	No	No	Yes

Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.22: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) Main	(2) Dundee	(3) Aberdeen	(4) Placebo
Public				
Treated Glasgow	0.559***	0.594***	0.522***	
	(0.139)	(0.180)	(0.178)	
Treated Edinburgh	0.129	0.173	0.093	
	(0.146)	(0.185)	(0.184)	
Placebo treatment				-0.041
				(0.133)
Passenger				
Treated Glasgow	0.191	0.024	0.334**	
	(0.137)	(0.178)	(0.170)	
Treated Edinburgh	0.372**	0.210	0.512***	
	(0.152)	(0.189)	(0.182)	
Placebo treatment				0.037
				(0.116)
Walk				
Treated Glasgow	0.323***	0.323**	0.312**	
	(0.121)	(0.155)	(0.150)	
Treated Edinburgh	0.325**	0.334**	0.316**	
	(0.128)	(0.161)	(0.156)	
Placebo treatment				0.068
				(0.095)
Other				
Treated Glasgow	-0.859***	-0.300	-1.360***	
	(0.316)	(0.467)	(0.386)	
Treated Edinburgh	-0.118	0.446	-0.628	
	(0.323)	(0.470)	(0.392)	
Placebo treatment				-0.272
				(0.309)
Observations	43169	37350	37930	99932
Pseudo R^2	0.091	0.086	0.088	0.076
Year fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes

Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Control group consist of only Dundee in Column 2
Control group consists of only Aberdeen in Column 3
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.23: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) Main	(2) Tram	(3) Within-city	(4) Unweighted	(5) Linear trend
Public					
Treated Glasgow	0.559***	0.562***	0.548***	0.523***	0.074
	(0.139)	(0.139)	(0.171)	(0.117)	(0.286)
Treated Edinburgh	0.129	0.053	0.041	0.136	-0.224
	(0.146)	(0.164)	(0.169)	(0.123)	(0.304)
Passenger					
Treated Glasgow	0.191	0.194	0.416**	0.202*	-0.576**
	(0.137)	(0.137)	(0.184)	(0.117)	(0.274)
Treated Edinburgh	0.372**	0.306*	0.303	0.286**	0.203
	(0.152)	(0.183)	(0.189)	(0.128)	(0.319)
Walk					
Treated Glasgow	0.323***	0.325***	0.392***	0.332***	0.166
	(0.121)	(0.121)	(0.143)	(0.104)	(0.247)
Treated Edinburgh	0.325**	0.242*	0.307**	0.307***	0.179
	(0.128)	(0.147)	(0.142)	(0.109)	(0.259)
Other					
Treated Glasgow	-0.859***	-0.857***	-0.966**	-1.048***	0.341
	(0.316)	(0.316)	(0.403)	(0.271)	(0.520)
Treated Edinburgh	-0.118	-0.159	-0.218	-0.185	0.123
	(0.323)	(0.347)	(0.405)	(0.281)	(0.514)
Observations	43169	43169	28328	43169	43169
Pseudo R^2	0.091	0.091	0.084	0.084	0.092
Year fixed effects	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes
Edinburgh tram control	No	Yes	No	No	No
Travel diary weights	Yes	Yes	Yes	No	Yes
Linear trend	No	No	No	No	Yes

Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.24: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) Main	(2) Rail
Public		
Treated Glasgow	0.559***	
	(0.139)	
Treated Edinburgh	0.129	
	(0.146)	
Passenger		
Treated Glasgow	0.191	0.174
	(0.137)	(0.137)
Treated Edinburgh	0.372**	0.368**
	(0.152)	(0.152)
Walk		
Treated Glasgow	0.323***	0.293**
	(0.121)	(0.121)
Treated Edinburgh	0.325**	0.321**
	(0.128)	(0.128)
Other		
Treated Glasgow	-0.859***	-0.788**
	(0.316)	(0.313)
Treated Edinburgh	-0.118	-0.033
	(0.323)	(0.322)
Bus		
Treated Glasgow		0.132
		(0.147)
Treated Edinburgh		0.047
		(0.151)
Rail		
Treated Glasgow		1.825***
		(0.397)
Treated Edinburgh		0.864**
		(0.430)
Observations	43169	43057
Pseudo R^2	0.091	0.098
Year fixed effects	Yes	Yes
City fixed effects	Yes	Yes
Individual controls	Yes	Yes

Standard errors in parentheses
Robust standard errors clustered at individual level
Outcome reference category: Car as driver
Public denotes public transport
Passenger denotes car as passenger
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.25: Current public transport fares by city

City	Mode	Operator	Ticket	Fare (GBP)
Glasgow	Bus	First Bus	Adult single	1.95
	Rail	ScotRail	Adult single	2.30
Edinburgh	Bus	Lothian Buses	Adult single	2.00
	Rail	ScotRail	Adult single	2.80
Dundee	Bus	XPlore Dundee	Adult single	2.20
	Rail	ScotRail	Adult single	2.50
Aberdeen	Bus	First Bus	Adult single	1.95
	Rail	ScotRail	Adult single	3.00

Sources: search of operator websites
Rail fares are for Glasgow Central to Queen's Park (Glasgow); Waverley to Haymarket (Edinburgh); Dundee to Balmossie (Dundee); and Aberdeen to Dyce (Aberdeen).

Table B.26: Regression difference-in-differences estimates of ride hailing effect on choice of main mode

	(1) Nested logit
Alone	
Treated Glasgow	0.763***
	(0.056)
Treated Edinburgh	0.789***
	(0.060)
Share	
Treated Glasgow	0.910
	(0.092)
Treated Edinburgh	1.315**
	(0.141)
Public	
Treated Glasgow	1.773***
	(0.169)
Treated Edinburgh	1.499***
	(0.148)
Other	
Treated Glasgow	1.112
	(0.373)
Treated Edinburgh	0.937
	(0.334)
Journeys	43169
Year fixed effects	Yes
City fixed effects	Yes
Individual controls	Yes

Exponentiated coefficients; Standard errors in parentheses
Outcome reference category: Car as driver
Public denotes public transport
Share denotes car as passenger
Sources: Author's analysis; SHS (2020)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.27: Nested logistic regression dissimilarity parameters

	(1)
/type	
Alone_tau	1.000
	[-2.510,4.510]
Share_tau	1.000
	[0.023,1.977]
Public_tau	0.965
	[0.909,1.021]
Active_tau	0.221
	[0.206,0.237]
Other_tau	1.000
	[-17.131,19.131]

95% confidence intervals in brackets
Sources: Author's analysis; SHS (2020)
Tau denotes dissimilarity parameter

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