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Investigating the effects of ridesourcing on the dynamics of household car ownership

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ABSTRACT

Car ownership influences car use, but the emergence of ridesourcing has reshaped this dynamic. The emergence of ridesourcing presents a dual possibility regarding car ownership: it can reduce the need for private car ownership by providing a viable alternative, or it can encourage car ownership by providing an opportunity to earn extra income through ridesourcing. Using the United Kingdom Household Longitudinal Study dataset from 2009 to 2019, this study examines how ridesourcing affects the changes in household car ownership. After controlling for various factors, our results suggest that households are less likely to acquire a car in the presence of ridesourcing while car disposal decisions are mainly driven by household composition and residential relocation factors. We also examine the heterogeneous effects that vary by different numbers of household cars and residential areas. Our results can inform transport authorities and policymakers when planning a sustainable transport system with reduced car dependency.

1. Introduction

Car ownership is among the most significant factors that trigger car use. Therefore, there is a long-standing interest in factors affecting car ownership and wider travel behaviour. Existing research suggests that the number of household cars is positively related to car use frequency (Van Acker and Witlox, 2010; Whittle et al., 2022). However, with its distinctive business model, ridesourcing has emerged as a game-changer in the personal mobility market within the last decade. Ridesourcing is a mobility service provided by Transport Network Companies (TNCs) that connects registered drivers with passengers and allows users to track and manage their trips through a smartphone application. By enabling access-based consumption against ownership-based consumption at a reasonable price and improved convenience (Paundra et al., 2020), ridesourcing appears to reformulate the well-established relationship between car use and car ownership.

Discerning the relationship between ridesourcing and car ownership is not straightforward. Having both service providers and riders be the users of private cars (Gong et al., 2017), the emergence of ridesourcing has the potential to affect the number of private cars in multiple directions. On one hand, large ridesourcing platforms, such as Uber and Lyft, promise to reduce private vehicle ownership by providing a cheap, reliable and convenient on-demand private ride as a viable alternative to personal cars (Hawkins,

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2018; Shontell, 2015). Therefore, ridesourcing has the potential to reduce car ownership by replacing personal cars. On the other hand, these platforms offer various promotions, such as discounts on car purchases or leasing from car manufacturers that have special agreements with TNCs, to prospective ridesourcing drivers to increase participation in their platforms (Brandom, 2013; Lutz, 2016; Si, 2018). In this case, it may encourage people to purchase cars to work as ridesourcing drivers to make extra income.

To date, existing studies mostly focused on the potential relationship between ridesourcing availability and household car numbers or intention to change their household car ownership, often carrying out cross-sectional analysis (e.g. Bansal et al., 2020; Das, 2020; Sabouri et al., 2020; Tang et al., 2020). However, investigating a change in travel behaviour requires observation of individuals' behaviour and changes in their life course and characteristics over time (Hanly and Dargay, 2000) because a change in one's travel behaviour is often encouraged by the change in their life course or context (Whittle et al., 2022). Cross-sectional datasets lack such information and thus provide only weak evidence for causal inference. Yet panel datasets containing this information over a period long enough to model trends in the outcome of interest before and after the 'intervention' are rarely available. In this study, we empirically investigate the impacts of availability of ridesourcing on changes in household car ownership using a large longitudinal dataset that contains rich information over a period from 2009 to 2019. Also, to the best of our knowledge, our study is the first to investigate the potential relationship between ridesourcing availability and car ownership at the household level using a longitudinal dataset. Furthermore, we investigate the heterogeneous effects of ridesourcing across different residential environments and household car ownership levels.

The rest of the paper is organised as follows. Section 2 summarises the findings from the relevant literature on the impacts of ridesourcing services on car ownership. Section 3 explains the methodology including the description of the study area and dataset, variables, and modelling approach. Section 4 presents the empirical results of a case study conducted in the United Kingdom and a discussion of the results. Finally, Section 5 draws conclusions.

2. Literature review

There is a well-established body of literature on the factors that determine variations in car ownership levels among individuals or households. These factors include the socioeconomic and demographic characteristics of individuals and households, life events (Müggenburg et al., 2015) and the 5Ds (density, diversity, design, destination accessibility, and distance to transit) of the built environment (Ewing and Cervero, 2010). However, the number of cars that the household owns is found to be state-dependent which suggests that the number of cars a household owns in the present strongly depends on the number of cars owned in the previous period (Hanly and Dargay, 2000; Simma and Axhausen, 2003). Therefore, properly investigating household car ownership and changes in car ownership levels requires longitudinal analysis over time, as well as the consideration of dynamic factors.

Using longitudinal datasets from different countries, studies in the relevant literature consistently found that households that experience a life event or a change in individual or household context are more inclined to change car ownership status (Clark et al., 2016; Prillwitz et al., 2006; Yamamoto, 2008). For example, using the United Kingdom Household Longitudinal Study (UKHLS), or 'Understanding Society', dataset, Clark et al. (2016) found that major life events such as changes in employment status and household composition, the birth of a child or driver's license acquisition significantly affect the decision to change household car ownership in the UK. Also, travel characteristics including trip distance (Whittle et al., 2022) and travel time with alternative transport modes (Clark et al., 2014) have a significant impact on UK households' decisions to change car ownership levels and mode use. However, in these studies, a substantial part of the variation in car ownership decisions remained unexplained which implies that other factors such as attitudes or personal choices play an important role (Clark et al., 2016).

In the last decade, ridesourcing has emerged as a disruptive innovation in personal mobility and it has clearly changed the way people travel. By providing on-demand private rides for a reasonable price with shorter waiting times, ridesourcing services quickly became very popular all around the world. Consequently, their impacts on various aspects, such as travel behaviour, traffic and environment have become the subject of discussions while ridesourcing platforms have promoted the idea that such services could lead to reduced reliance on personal vehicle ownership (Hawkins, 2018; Shontell, 2015).

Disaggregate studies in the early stages of ridesourcing services mostly relied on stated preference surveys and focused on the US. These studies suggest that although some people have started to drive less frequently after using ridesourcing, most people have not made any changes in their car ownership status (Clewlow and Mishra, 2017; Rayle et al., 2016) which is expected as it requires time for people to adopt innovations. Also, ridesourcing services tend to be used occasionally, such as for leisure trips, while only a small portion of ridesourcing trips are for daily, regular trips, such as commuting which are unlikely to result in changing car ownership (Rayle et al., 2016). More recently, using the 2017 National Household Travel Survey (NHTS) dataset, studies consistently found that there is a negative relationship between number of household cars and ridesourcing use frequency in the US (Blumenberg et al., 2021; Sabouri et al., 2020; Schaller, 2018; Wu and MacKenzie, 2021). However, because of data limitations, these studies are unable to assess the direction of the relationship between ridesourcing use frequency and the number of vehicles owned, i.e., whether the former has an effect on the latter or vice-versa. More recently, Batur et al. (2023) and Wang et al. (2021) investigated this possible bidirectional relationship between car ownership and ridesourcing use in the US, using a survey dataset and 2017 NHTS dataset respectively, and suggested that there is an inverse effect in both directions.

Studies in China present mixed findings. A survey conducted in Hangzhou, China revealed that 10 % of survey participants with no car purchase plans before ridesourcing services stated their intentions to buy a new car (Zheng et al., 2019). On the other hand, in other studies, respondents in China expressed their intentions to postpone or completely give up purchasing a car after starting to use ridesourcing (Tang et al., 2020; Yang et al., 2022; Zheng et al., 2019).

However, studies from both the US and China, which utilise longitudinal datasets of actual vehicle registration and licensing data, present contradictory findings with the findings of the disaggregate studies discussed above. In China, in contrast to the people's stated reluctance to purchase a car, car registration numbers show an increase after the introduction of ridesourcing (Gong et al., 2017; Guo et al., 2020, Guo et al., 2019, Guo et al., 2018). Similarly, in the US, studies show that car ownership has increased in urban areas following the introduction of ridesourcing, while no effect has been observed in rural areas (Ward et al., 2021, 2019).

Existing literature regarding the impact of ridesourcing on car ownership mostly focuses on the US and China, and only a few studies have been conducted in different countries. Among these, Paundra et al. (2020) found that ridesourcing has caused an increase in car numbers in Indonesia, while Wadud and Namala (2022) found the opposite effect in India. After the introduction of motorcycle-based ridesourcing, which is the common form of ridesourcing especially in South-Southeast Asia and Africa, motorcycle numbers decreased in Indonesia (Paundra et al., 2020), but increased in Dhaka, Bangladesh (Wadud, 2020). These findings also show that the effect of ridesourcing on vehicle ownership significantly varies across countries. However, in Accra and Kumasi (Ghana), Paris (France) and Bangkok (Thailand), studies in which people are asked about their intentions to purchase or shed a car in the presence of ridesourcing, consistently found that ridesourcing is not the main factor that encourages people to give up car ownership but in the presence of adequate public transit services it has potential to reduce vehicle ownership (Acheampong et al., 2023; Bekka et al., 2020; Thaithatkul et al., 2023).

The impacts of ridesourcing on car ownership in Great Britain have only recently been examined at the aggregate level, specifically the local authority district (LAD)[1] level. Results suggest that controlling for the built environment (5Ds), socio-economic and demographic characteristics, ridesourcing services have caused a reduction in car ownership in rural LADs and London, while no statistically significant change has been observed in urban LADs and metropolitan districts (Bilgin et al., 2023a). The authors conclude that ridesourcing services may help reduce car ownership only when they are part of an environment which is properly regulated and supports multimodality and sustainable mode use with advanced public transport services and built environment characteristics. Nevertheless, individual and household characteristics and major life events are proven to have an important role when UK households decide to acquire or shed a car (Clark et al., 2014). Disaggregate models better reflect behavioural patterns, while aggregate data is unable to capture the heterogeneity that arises from these varied characteristics among households and individuals (Bhat and Pulugurta, 1998). Therefore, it is important to examine the motivations behind this decision at the finer level.

Concerning the existing research reviewed here, we have four main contributions. First, previous studies mostly focus on certain geographies, specifically the US and China, and there is a lack of knowledge regarding the effects of ridesourcing on vehicle ownership in other countries. However, findings from the emerging literature suggest diverse outcomes which show the effects of ridesourcing services differ from place to place. This study focuses on the case of the UK, where there is a lack of evidence. Secondly, existing studies using disaggregated data rely on cross-sectional datasets or surveys and as such they lack the ability to control for long-term behavioural patterns. Thirdly, studies using aggregate longitudinal datasets, on the other hand, are unable to address heterogeneity among individuals. Using a large panel dataset that contains rich information allows us to investigate the relationship between ridesourcing and household car ownership while controlling for the effects of various individual and household characteristics, major life events and the built environment characteristics. This approach uniquely positions our study as the first study using a large disaggregate longitudinal dataset for this purpose. Lastly, recent research shows that the effect of ridesourcing on car ownership varies significantly across different residential settings (Guo et al., 2020; Ward et al., 2019; Zhong et al., 2020), this is also consistent within the context of Great Britain (Bilgin et al., 2023a). Our study adds to a limited number of studies that investigated heterogeneity in the impacts of ridesourcing on vehicle ownership. Also, comparing our findings at the disaggregate level with the findings at the aggregate (LAD) level presented in Bilgin et al. (2023), we aim to present a more comprehensive picture of the effects of ridesourcing on car ownership in the UK.

3. Methodology

3.1. Data, sample characteristics and representativeness

Our study focuses on the case of the United Kingdom. The main dataset used in this study is the United Kingdom Household Longitudinal Study (UKHLS or Understanding Society Survey), which is a longitudinal household survey carried out yearly in the UK, starting from 2009 (University of Essex, 2022). In our study, we use the data from the pre-pandemic period, which covers the first 11 waves of UKHLS over the period spanning 2009–2019. UKHLS contains rich information on individual and household-level socio-economic and demographic characteristics of the members of over 40,000 UK households who are interviewed at regular 12-month intervals.

UKHLS is a probability survey with a complex sample design and most of the sub-samples were clustered and stratified with unequal selection probabilities.[2] To account for the sampling design, we include the clustering and stratification variables in our analysis.[3] The first wave of UKHLS includes 50,994 individuals from 40,000 households, i.e. it includes multiple individuals from the same household. Over time some members leave the original household and form a new household or new members are involved in

[1] Local Authority District (LAD) is a geographical unit in Great Britain for which a local government body is responsible.

[2] Details for the UKHLS study design can be found in the Understanding Society website via https://www.understandingsociety.ac.uk/documentation/mainstage/user-guides/main-survey-user-guide/study-design/.

[3] By accounting for the complex survey design and calculating robust standard errors in our analysis, we also address potential issues of heteroscedasticity and autocorrelation.

households and cause a change in the original household composition. Therefore, it is discussed that the change in the household car numbers should not be inferred by ignoring the dynamic nature of household structure (Clark et al., 2016). Also, the UKHLS survey is designed to follow individuals over time, not households, so it is not possible to follow the households and choose them as the unit of analysis.[4] On the other hand, as the dataset provides the number of household cars which is the same for each member of a household, modelling each individual separately leads to bias in the results due to multiple counting. Hence, we kept only the reference person from each household in the sample and adopted the head-of-household[5] approach which is frequently employed in similar research (Haque et al., 2019). Hence, we use household as the panel unit and year as the time unit.

Given the restriction in the availability of variable of interest (ridesourcing availability)-which will be elaborated on in the next section, the sample analysed included only households residing in LADs with a non-missing ridesourcing variable. Longitudinal weights provided in the UKHLS dataset deal with potential sampling errors, unequal selection probabilities and differential nonresponse. However, the exclusion of households with missing ridesourcing variables from the whole sample is non-random which potentially results in representativeness issues in the subsample. To reduce the potential bias arising from the non-random exclusion in the panel data setting and to ensure representativeness to the population, we employed Iterative Proportional Fitting (IPF). IPF is a model-based approach that uses known population and sample characteristics to adjust the sample to reflect the population by iteratively assigning a weight to each individual in the sample until the weights converge (Anderson et al., 2015). The final weights are a combination of survey weights provided by the data owner and IPF weights. In that way, we obtained a sample representative of the UK population over the period spanning 2009–2019. Table 1 presents the proportion of households from three distinct samples (the full sample with UKHLS weights, the subsample[6] with UKHLS weights, and the subsample with final weights), categorised by the household car numbers and the change in the number of household cars observed in the subsequent period.[7]

3.2. Variables

The dependent variables are the acquisition and disposal of household cars[8] which are derived from the self-reported number of cars "owned or regularly available to the household" in the UKHLS dataset. Earlier studies revealed the stability of car ownership state in consecutive periods (Simma and Axhausen, 2001; Thøgersen, 2006). In our case, change in household car ownership follows a similar pattern, with most households typically maintaining their ownership status between consecutive periods. Also, Dargay and Hanly's (2007) observation that the transaction between one car and two cars (in both directions) is the most frequent change pattern is valid in our case. Table 2 presents the household car ownership transaction in two consecutive observations.

The ridesourcing variable is the main independent variable in our models. The UKHLS does not include a question about ridesourcing use or travel mode choice including ridesourcing as an alternative. Therefore, we used the availability of ridesourcing services to represent the effect of ridesourcing. It is a dummy variable that indicates whether ridesourcing services are available in a given LAD in the given year and relies on the ridesourcing launch dates. We collected data on ridesourcing launch dates from existing literature (specifically Kirk et al. 2020) which is mostly based on the entry announcements of TNCs on their websites, local newspapers, and through Freedom of Information (FoI) requests. In response to our FoI inquiries, licensing offices of many LADs reported the absence of ridesourcing operations within their area. However, our practical tests using smartphone applications of Uber, Ola, or Bolt, allowed us to successfully request rides in many of these LADs. After a thorough examination of both the app-based findings and the previously mentioned three sources, we found no evidence of active ridesourcing services in 13 LADs during our study period from 2009 to 2019. Consequently, we have proceeded with the assumption that these LADs did not have ridesourcing services available in the timeframe considered for our analysis. Finally, we include observations from 124 LADs shown in Fig. 1.

The decision to change household vehicle ownership status or numbers is influenced by a variety of dynamic factors. These include changes in travel patterns or requirements, changes in the built environment, changes in financial situation or employment, and life cycle events (Clark et al., 2016; Oakil et al., 2014). Studies indicate that changes in household car ownership often coincide with these dynamic factors, occurring consecutively or simultaneously. Moreover, studies using the UKHLS dataset have also shown that major life events are important determinants of change in car ownership status (Clark et al., 2016; Dargay and Hanly, 2007). Hence, we include residential relocation, change in employment status including retirement, birth or adoption of a child, change in cohabitation status, and change in the number of adults in the household as life events or change variables. We derived life event variables from the UKHLS dataset. We also include the household head's age and age squared as individual characteristics and the equivalised household

[4] In the UKHLS dataset, each individual is assigned a unique personal ID number that remains consistent across all waves. However, due to the dynamic nature of household formation and dissolution, and the specific design of the study, households are assigned different identification numbers in each wave.

[5] In our sample, we represent each household solely by the household reference person, or the household head, by excluding all other household members. Consequently, we will refer to each panel unit in the sample as a 'household' throughout the remainder of the text.

[6] The subsample is obtained after excluding individuals who reside in LADs where the ridesourcing variable is missing from the full sample.

[7] Descriptive statistics are presented in Appendix A.

[8] While in theory, car acquisition and car disposal can occur in the same survey year through purchasing and selling a car or cars and may result in a net zero change in the number of household cars in that year, we are unable to consider this, as the only information available to us is the total number of household cars in each survey wave. Therefore, in this study, the term 'car acquisition' implies a net increase in the number of household cars, while the term 'car disposal' implies a net decrease in the number of household cars compared to the previous observation. While this is a limitation, purchasing and disposing of cars are relatively rare events for most households, so we believe that this does not overly affect our analysis.

Table 1
Distribution of three samples based on the household car numbers and change in the number of household cars.

	Number of household cars				Change in the number of household cars		
	0 car	1 car	2 cars	3 + cars	No change	Increase	Decrease
Full sample with UKHLS weights	17.3 %	37.7 %	32.4 %	12.5 %	80.9 %	10 %	9.1 %
Subsample with UKHLS weights	28.6 %	41.7 %	23.5 %	6.3 %	83.6 %	7.9 %	8.4 %
Subsample with final weights	20 %	40.6 %	30.1 %	9.3 %	81.4 %	9.2 %	9.4 %

Table 2
Transactions of household car ownership in two consecutive observations (percentages refer to the whole sample).

t \ t+1	0 car		1 car		2 cars		3 or more cars	
	Freq.	Percent.	Freq.	Percent.	Freq.	Percent.	Freq.	Percent.
0 car	20706	24.21%	2082	2.43%	154	0.18%	32	0.04%
1 car	1876	2.19%	33625	39.32%	3009	3.52%	238	0.28%
2 cars	134	0.16%	2567	3%	15410	18.02%	1268	1.48%
3 or more cars	19	0.02%	221	0.26%	1045	1.22%	3123	3.65%

income[9] (in real terms), equivalised household income squared,[10] number of household cars, number of employed adults in the household, and number of kids in the household to represent household characteristics. We also controlled the educational attainment of household heads which is found among important determinants of both car ownership (Clark et al., 2016) and the adoption of ridesourcing services (Mohamed et al., 2020; Rayle et al., 2016).

Built environment variables from various sources were linked to the UKHLS dataset using LSOA (lower layer super output area[11]) identifiers that are provided in the special license version of the dataset. However, due to limitations in the availability of the LSOA-level built environment variables, we utilise these variables at a more aggregate level, specifically at the LAD level. LADs represent local government units comprised of LSOAs. We include population and job density (both in logarithm),[12] number of buses per 1000 people, and metro, light rail or tram availability as built environment-related control variables. We also included residential environment variables (rural LSOA, urban LSOA, and London boroughs) to control for potential unobserved characteristics of these areas. Finally, we included the vehicle price index and real fuel price to represent the cost of car ownership and use.

Details of the variables included in our models and the corresponding data sources can be found in Table 3.

3.3. Modelling approach

To investigate the change in the number of household cars in the presence of ridesourcing, we constructed two models. The first one, the car acquisition model, models the effect of ridesourcing on the decision to increase the number of household cars and uses the whole sample. The second one, the car disposal model, models the effect of ridesourcing on the decision to reduce the number of household cars. People who did not own a car in the period preceding the analysis period are excluded from the car disposal model, as they have no opportunity to dispose of a car.

Dependent variables in both models are binary (car acquisition/disposal and no car acquisition/disposal) and our interest focuses on the increase or decrease in the number of household cars over time within households. Therefore, we employed the fixed-effects logit model.[13]

[9] We calculated equivalised household income using the OECD equivalisation factor (OECD, 2011).
[10] Previous studies have shown a non-linear relationship between vehicle ownership and age and income variables (Dargay and Vythoulkas, 1999). Therefore, we also include age- and income-squared terms in our analysis.
[11] LSOAs refer to geographical areas for census statistics that comprise 400–1200 households or 1000–3000 persons in England and Wales (Office for National Statistics, n.d.). Data zones (DZs) which comprise 500–1000 persons are corresponding geographical zones used in Scotland (Scottish Government, n.d.), while Super Output Areas (SOAs) are the corresponding geographical areas for census statistics in Northern Ireland.
[12] We include non-linear terms based on the theoretical reasoning and prior empirical findings. While this approach may not capture all potential complexities in the relationships among variables, it is widely accepted in the literature, particularly in studies with an exploratory focus.
[13] Using an multinomial logit (MNL) model with households experiencing no change in car numbers as the reference group could be considered as an alternative approach. However, the primary reason we run two separate models (one for car acquisition and another for car disposal) is that households who did not acquire a car and those who did not dispose of a car are fundamentally different, even though they both fall under the 'no change' category. Combining these two distinct groups into a single reference category would mask the differences between these groups and likely introduce bias, notably since all coefficients in a MNL model are relative to the reference category.

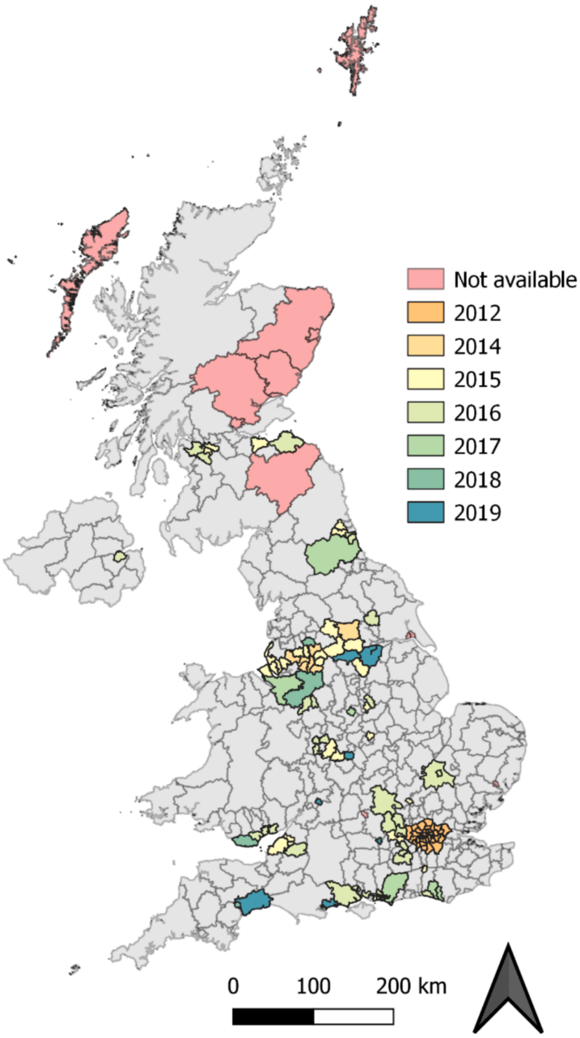

Fig. 1. LADs included in this study with respective ridesourcing launch years.

$$ACQ_{it} = \frac{exp(RS_{it}\gamma + \sum_j X_{itj}\beta_j + \alpha_i + \theta_t)}{1 + exp(RS_{it}\gamma + \sum_j X_{itj}\beta_j + \alpha_i + \theta_t)} \tag{1a}$$

$$DISP_{it} = \frac{exp(RS_{i(t-1)}\gamma + \sum_j X_{itj}\beta_j + \sum_l Z_{i(t-1)l}\delta_l + \alpha_i + \theta_t)}{1 + exp(RS_{i(t-1)}\gamma + \sum_j X_{itj}\beta_j + \sum_l Z_{i(t-1)l}\delta_l + \alpha_i + \theta_t)} \tag{1b}$$

and,

$$ACQ_{it} = \frac{exp\left(\sum_{k,m}(RS_{it} \times RA_{itk} \times HC_{i(t-1)m})\vartheta_{km} + \sum_j X_{itj}\beta_j + \alpha_i + \theta_t\right)}{1 + exp\left(\sum_{k,m}(RS_{it} \times RA_{itk} \times HC_{i(t-1)m})\vartheta_{km} + \sum_j X_{itj}\beta_j + \alpha_i + \theta_t\right)} \tag{2a}$$

$$DISP_{it} = \frac{exp\left(\sum_{k,m}(RS_{i(t-1)} \times RA_{itk} \times HC_{i(t-1)m})\vartheta_{km} + \sum_j X_{itj}\beta_j + \sum_l Z_{i(t-1)l}\delta_l + \alpha_i + \theta_t\right)}{1 + exp\left(\sum_{k,m}(RS_{i(t-1)} \times RA_{itk} \times HC_{i(t-1)m})\vartheta_{km} + \sum_j X_{itj}\beta_j + \sum_l Z_{i(t-1)l}\delta_l + \alpha_i + \theta_t\right)} \tag{2b}$$

where ACQ_{it} and $DISP_{it}$ are the probability of household *i* acquiring and disposing of a carat time *t*, respectively. Eqs. (1a) and (1b) represent the average effect of ridesourcing on car ownership decisions of households across the UK. RS_{it} is the dummy variable that represents the availability of ridesourcing in LAD where household *i* resides at time *t* and *t-1* with corresponding coefficient γ, in car acquisition and car disposal models respectively. X_{itj} is the *jth* control variable for household *i* at time *t* with the corresponding coefficient β. $Z_{i(t-1)l}$ is the *lth* control variable for household *i* at time *t-1* with the corresponding coefficient δ, representing the delayed

Table 3
Description of variables used in the analysis.

Variable		Definition	Data source
Dependent variables			
Acquisition of a car	No car acquisition	The household has not acquired a car/cars	UKHLS (derived)
	Car acquisition	The household has acquired a car/cars	
Disposal of a car	No car disposal	The household has not disposed of a car/cars	UKHLS (derived)
	Car disposal	The household has disposed of a car/cars	
Predictor			
Ridesourcing availability		Availability of ridesourcing services in local authority district where the household resides at the given year	(Bilgin et al., 2023a)
Control variables			
Individual characteristics			
Age		The age of the household head in years	UKHLS
Age squared		Square of the age of the household head in years	UKHLS (derived)
Education level		The education level of the household head	UKHLS
Household characteristics			
Number of children		The number of children in the household	UKHLS
Number of employed adults		The number of adults who are in paid employment	UKHLS
Equivalised household income		Equivalised net household income in real-term	UKHLS (derived)
Equivalised household income squared		Square of the equivalised net household income	UKHLS (derived)
Household car ownership		Number of household cars (0, 1, 2 or 3 or more cars)	UKHLS (derived)
Built environment characteristics			
Residential location		Whether the household resides in London, other urban areas or rural areas	UKHLS
Population density (log)		The log-transformed population density of the local authority district	(Office for National Statistics, 2020a)
Job density (log)		The log-transformed job density of the local authority district	(Office for National Statistics, 2020b)
Number of buses in the local authority per 1000 people		The number of buses in the local authority district per 1000 people	(Department for Transport, 2021)
Rail transport availability		Availability of light rail, tram or metro in the local authority district	Various sources
Cost of car ownership and use			
Real fuel price		Fuel price in real terms	(Department for Business Energy and Industrial Strategy, 2022)
Vehicle price index		Vehicle price index	(Office for National Statistics, (2021a, 2021b))
Life events			
Residential relocation		Whether the household has relocated between or within rural LSOAs, urban LSOAs and London	UKHLS (derived)
Employment status change		Whether the household head has experienced a change in employment status, including retirement	UKHLS (derived)
Birth or adoption of a child		Whether the household has had or adopted a child since the last wave	UKHLS (derived)
Change in the number of adults in the household		Whether an adult joined or left the household since the last wave	UKHLS (derived)
Change in cohabitation		Whether a cohabitation has been formed or dissolved since the last wave	UKHLS (derived)

effect of these factors on car disposal. α_i and θ_t represent household and year fixed effects, respectively.

Eqs. (2a) and (2b) model the varying effects of ridesourcing across different residential areas and levels of household cars. RA_{itk} is a categorical variable for residential area *k* (rural, urban, metropolitan districts or London) where household *i* resides at time *t*. $HC_{i(t-1)m}$ is a categorical variable that classifies household *i* based on the number of cars *m* in household *i* (zero-car,[14] single-car, two cars, three or more cars) at time *t-1,* one period before the analysis period *t.* The interaction of *RS, RA* and *HC* shows how the effect of ridesourcing availability varies across different residential environments and different car ownership levels.

The decision of TNCs on whether and when to enter into the LADs in the UK may be strategic which may raise endogeneity issues. In this case, ridesourcing entry may be endogeneous to car ownership as TNCs may decide to enter LADs based on the car ownership level. However, the largest global TNCs, including the ones that we consider in our research, described their entry decisions as "more opportunistic than strategic" (Ward et al., 2019). To address the endogeneity issue, we calculated the correlation between ridesourcing entry into LADs and the log of the number of vehicles per 1000 people in LADs. To isolate the change in car ownership from the effect of time, we used the change in the number of vehicles per 1000 people and performed a *t*-test. The results showed that the difference between car ownership in LADs with and without ridesourcing is not statistically significant ($p = 0.1663$), hence, suggesting the ridesourcing entry into LADs is exogenous to car ownership in the LADs.

[14] Car disposal models do not include zero-car group because of the exclusion of this group from the model as was mentioned in the begining of this section.

4. Results and discussion

The best fit fixed effects logit models for car acquisition and car disposal probabilities are presented in Table 4. Baseline models follow the specifications presented in Eqs. (1a) and (1b). The real fuel price variable is excluded from the analysis because of multicollinearity with the year-fixed effects.

We consider potential anticipation between the occurrence of life events and car acquisition and car disposal decisions following the findings in the literature which suggest that residential relocation and change in employment status (including retirement) occur before the car disposal, while household formation and dissolution processes (including cohabitation formation and dissolution) and change in the number of adults in the household e.g. offspring reaching adulthood have a significant and simultaneous effect on car disposal (Oakil et al., 2014). We also used 1-year lagged ridesourcing variable in car disposal models, as it may require some time for households to decide to get rid of their cars in the presence of an alternative. Based on this reasoning, we present models with level variables for car acquisition and models with the aforementioned lagged variables for car disposal.[15] Note that the sample analysed in car disposal models excludes observations from households with zero cars in the preceding period.

The results of the baseline models suggest that the availability of ridesourcing is associated with a lower likelihood of acquiring a car in a statistically significant way, while its association with disposing of a car is not statistically significant. Variation between the impacts on car acquisition and car disposal decisions is not unexpected as there is a recognised asymmetry between decisions of car acquisition and car disposal in the literature. Specifically, the utility lost from disposing of a car is greater than the utility gained from acquiring one, with this difference being even more noticeable when comparing the acquisition of the first car to the disposal of the only car in a household (Roorda et al., 2009).

Our results support this and are consistent with the findings that multiple-car households are more likely to dispose of one (or more) of their cars when compared to single-car households, while they are less likely to acquire another one (Hanly and Dargay, 2000; Oakil et al., 2014; Prillwitz et al., 2006). This supports the hypothesis that multiple-car ownership fluctuates more than single-car ownership (Dargay and Hanly, 2007). Then, the availability of ridesourcing services may encourage households to shed their extra cars instead of their sole household car. Similarly, ridesourcing could lead households to forego the acquisition of additional cars. Furthermore, the effect of ridesourcing may vary between households residing in different residential environments which is the case in Great Britain as Bilgin et al. (2023a) have shown using geographically aggregated datasets. Therefore, we investigate the potential heterogeneous effect of ridesourcing availability across different residential environments and varying levels of car ownership. We follow the specifications presented in Eqs. (2a) and (2b) and include three-way interactions in the baseline models. However, for the sake of brevity, in the main text, we focus on the estimated odds ratios for the variable of interest and from the combination of the main effects and interaction effects for different areas by a varying number of household cars in the presence of ridesourcing[16] which are presented in Table 5 and Table 6, respectively. The model estimation results for confounders are presented in Appendix B.

The results of the heterogeneous effect model of car acquisition suggest that UK households residing in urban areas (including London, metropolitan districts and other urban areas) are less inclined to acquire another car in the presence of ridesourcing if they already own three or more cars. In other urban areas, this effect is observed also for two-car households The reduced likelihood of car acquisition among multi-car households in these areas is intuitive, as urban areas are generally characterised by better accessibility and public transport services that ridesourcing can complement, than rural areas. As such, ridesourcing appears to reduce the need for additional cars by filling the gaps in the existing transport system and complementing public transportation in these areas. On the other hand, in rural areas, which are often characterised as more car-dependent, the availability of ridesourcing has not caused a statistically significant change in car acquisition regardless of the number of cars in the household. This may suggest that the level of ridesourcing services provided in rural areas which is often less intense than in urban areas is not effective enough to influence households to stop or motivate acquiring a car in these areas. Consistent with the baseline models, the availability of ridesourcing has a statistically insignificant effect on the likelihood of disposing of a car regardless of the type of residential area and the number of cars in the household. This finding is in line with the studies in the existing literature that suggest ridesourcing is not an effective motivator by itself for people to discard their cars (Bekka et al., 2020). We also calculate the marginal effects of ridesourcing availability on the probability of increasing and decreasing the number of cars in the household. Table 7 presents the results for the baseline models and heterogeneous effect models respectively. The results for marginal effect estimates suggest that the availability of ridesourcing has statistically insignificant effects on the probability of changing, both increasing and decreasing, the number of cars in the household in the UK despite the statistically significant odds ratios for car acquisition models. In such cases, it is recommended to interpret the results based on the structural models rather than marginal effects (Greene, 2018). Therefore, in the rest of the paper, the discussion will be based on the odds ratios obtained from the structural models.

We can compare the results of this study with the findings regarding the effects of ridesourcing on aggregate (LAD) level vehicle ownership (Bilgin et al., 2023a) and Private Hire Vehicles (PHVs), including ridesourcing, numbers (Bilgin et al., 2023b). Our results support that the introduction of ridesourcing may help reduce vehicle ownership across the UK (Bilgin et al., 2023a) by potentially

[15] These models also perform better in terms of goodness of fit statistics than other alternatives.

[16] Odds ratios for the combination of the main effect and interaction effects can be obtained in two ways. The first approach involves calculating the linear combination of the estimated coefficients for the main effect of ridesourcing and the interaction terms involving household car numbers, area groups, then exponentiating this combined coefficient to obtain the odds ratios. The second approach multiplies the individual odds ratios of the main effect of ridesourcing and each relevant interaction term's odds ratio to get the combined effect. We crosschecked the results by applying both methods. Finally, the significance of these estimates was tested using the Wald test.

Table 4
Fixed effects logit model results for the probability of acquiring or disposing of a car.

		Car acquisition model (ref: no car acquisition)		Car disposal model (ref: no car disposal)	
		OR	t-stat.	OR	t-stat.
Ridesourcing availability				(1-year lagged)	
Available		0.656**	−2.13	0.631	−1.11
Household car numbers (Zero-car)		Reference category			
	One car	0.029***	−8.91	Reference category	
	Two cars	0.001***	−12.89	66.389***	13.79
	Three or more cars	0.000***	−15.57	1778.29***	18.14
Residential environment (ref: Urban LAD)					
	Rural LAD	1.115	0.19	0.931	−0.11
	Metropolitan districts	0.490	−0.72	2.498	0.45
	London	0.989	−0.01	2.209	0.25
Residential relocation (ref: no relocation)				(1-year lagged)	
	From rural LSOA to urban LSOA	0.349	−0.73	0.963	−0.05
	From urban LSOA to rural LSOA	2.577	1.39	4.786	1.21
	From urban LSOA to London	14.525	1.54	0.828	−0.17
	From London to rural LSOA	5.999	1.41	7.92e-10***	−17.34
	From London to urban LSOA	4.56e6***	8.53	–	–
	Within the same area group	1.029	0.08	0.560*	−1.83
Age		0.803	−0.99	0.739	−1.14
Age squared		0.997***	−4.70	1.005***	4.90
Equivalised household income (1000)		1.179**	1.99	0.941	−1.37
Equivalised household income squared		0.990**	−1.95	1.001	1.56
Education level (ref: No tertiary education qualification)		1.316	0.16	0.894	−0.14
Number of kids in the household		0.801	−1.27	1.100	0.58
Number of employed people in the household		2.924***	9.29	0.539***	−5.88
Population density (log)		0.828	−0.53	0.992	−0.03
Job density (log)		0.531	−1.09	0.861	−0.22
Number of buses per 1000 people		0.926	−0.73	0.780**	−2.15
Rail transport availability		1.098	0.16	0.103	−0.94
Vehicle price index		1.508	1.72	1.165	0.57
Change in number of adults (ref: No change)					
	Adult joined	1.551***	2.84	1.001	0.00
	Adult left	1.094	0.25	6.108***	6.94
Birth or adoption of a child					
	Yes	2.016**	2.00	1.265	0.92
Change in cohabitation status (ref: No change)					
	Cohabitation formed	2.839***	3.11	2.362	1.08
	Cohabitation dissolved	1.172	0.55	2.070*	1.83
Change in employment status (ref: No change)				(1-year lagged)	
	Employment gained	0.621	−1.60	1.512	1.48
	Employment lost	2.019**	2.01	0.922	−0.27
	Became retired	1.764	1.24	1.003	−0.01
Year fixed effect		Yes		Yes	
Unweighted sample		45,977		38,798	
Weighted sample		5327.4		3908.9	
AIC		15,964		8745.7	
BIC		16249.8		8995.6	
McFadden's pseudo-R^2		0.36		0.47	

Statistically significant *** at 99%, ** at 95%, * at 90%.

discouraging households residing in in urban areas from buying additional cars. However, while Bilgin et al. (2023a) suggest a reduction in vehicle ownership in rural areas despite the increase in PHV numbers (Bilgin et al., 2023b), our study found a statistically insignificant effect for changes in the number of cars in the household. A reduction found in the number of vehicles at the aggregate level may potentially be because local PHV companies discard existing vehicles without replacement after the introduction of ride-sourcing which makes the already smaller taxi market in rural areas when compared to urban areas more competitive and less profitable.

The effects of other factors are in line with the findings in the relevant literature. The impact of age and age-squared variables are in line with the relevant literature and reflect the traditional life-cycle concept (Dargay, 2002; Prillwitz et al., 2006). The likelihood of acquiring a car increases as equivalised income increases and after reaching its peak it starts to decrease which implies household car ownership reaches its saturation after some point. A positive relationship between income and car acquisition is expected as higher income enables easier car purchase and use (Oakil et al., 2014). Income variables have no statistically significant effect on car disposal decisions. The asymmetry between the effect of income on car acquisition and car disposal is recognised in the relevant literature (Dargay, 2001; Prillwitz et al., 2006).

The effects of most household composition-related factors on car acquisition and car disposal decisions are in the expected

Table 5
Fixed effects logit model results for the likelihood of acquiring or disposing of a car by different levels of initial household car ownership across different residential areas.

	Car acquisition model (ref: no car acquisition)		Car disposal model (ref: no car disposal)	
	OR	t-stat.	OR	t-stat.
Ridesourcing availability	0.825	−0.31	0.531	−1.52
Household car numbers (Zero-car)				
One car	0.035***	−5.46		
Two cars	0.004***	−6.84	31.239***	7.15
Three or more cars	0.001***	−7.90	1794.098***	10.86
Ridesourcing × Household car numbers				
Available × One car	0.865	−0.23		
Available × Two cars	0.409	−1.03	1.402	0.71
Available × Three or more cars	0.357	−1.49	1.264	0.43
Residential environment (ref: Urban LAD)				
Rural LAD	0.395	−1.09	0.111***	−2.99
Metropolitan districts	0.663	−0.50	1.233	0.11
London	1.702	0.44	0.999	−0.00
Ridesourcing × Residential environment				
Available × Rural LAD	0.396	−1.09	4.233*	1.94
Available × Metropolitan districts	0.663	−0.50	1.012	0.02
Available × London	1.702	0.44	1.537	0.69
Residential environment × Household car numbers				
One car × Rural LAD	0.341	−0.97		
Two cars × Rural LAD	0.153	−1.54	19.058***	4.04
Three or more cars × Rural LAD	0.060**	−2.04	4.666	1.64
One car × Metropolitan districts	0.638	−0.49		
Two cars × Metropolitan districts	0.144*	−1.84	2.674	1.45
Three or more cars × Metropolitan districts	0.116	−1.64	0.973	−0.03
One car × London	0.121**	−1.97		
Two cars × London	0.012***	−2.75	4.094	1.44
Three or more cars × London	0.057*	−1.78	2.519	0.58
Ridesourcing × Residential environment × Household car numbers				
Available × One car × Rural LAD	2.029	0.78		
Available × Two cars × Rural LAD	3.653	1.23	0.177*	−1.93
Available × Three or more cars × Rural LAD	5.251*	1.74	0.190	−1.61
Available × One car × Metropolitan districts	2.149	0.85		
Available × Two cars × Metropolitan districts	3.204	1.12	1.078	0.10
Available × Three or more cars × Metropolitan districts	1.344	0.29	1.063	0.08
Available × One car × London	0.873	−0.11		
Available × Two cars × London	3.857	0.85	0.326	−1.47
Available × Three or more cars × London	0.336	−0.72	0.358	−1.23
Year-fixed effect	Yes		Yes	
Unweighted sample	45,977		38,119	
Weighted sample	5327.4		3908.9	
AIC	15566.5		8650.7	
BIC	16025.3		9015.4	
McFadden's pseudo-R^2	0.36		0.48	

Statistically significant *** at 99%, ** at 95%, * at 90%.

Table 6
Estimated odds ratios from the combination of the main effects and interaction effects for different areas by a varying number of household cars in the presence of ridesourcing with t-stats in parentheses.

	Car acquisition				Car disposal		
Area	0 car	1 car	2 cars	3 + cars	1 car	2 cars	3 + cars
London	1.404	1.061	2.218	0.168**	0.816	0.373	0.369
	(0.34)	(0.14)	(0.90)	(−1.96)	(−0.42)	(−1.16)	(−1.07)
Metropolitan districts	0.547	1.017	0.718	0.262**	0.537	0.813	0.722
	(−1.14)	(0.04)	(−1.15)	(−2.36)	(−1.38)	(−0.46)	(−0.82)
Other urban LADs	0.825	0.713	0.338***	0.294***	0.531	0.744	0.671
	(−0.31)	(−1.03)	(−2.67)	(−3.23)	(−1.52)	(−1.03)	(−0.99)
Rural LADs	0.326	0.573	0.488	0.611	2.247	0.559	0.540
	(−1.63)	(−1.51)	(−1.56)	(−1.07)	(1.31)	(−1.31)	(−0.84)

Statistically significant *** at 99%, ** at 95%, * at 90%.

Table 7
Marginal effects of ridesourcing on car acquisition and disposal on average and in different areas and car ownership level with t-stats in the parentheses.

	Car acquisition (%)				Car disposal (%)		
Average effect	−0.266 (−0.33)				−0.002 (−0.05)		
Heterogeneous effect	0 car	1 car	2 cars	3 + cars	1 car	2 cars	3 + cars
London	0.337 (0.18)	0.150 (0.14)	2.391 (0.48)	−6.440 (−0.38)	−0.010 (−0.05)	−5.49e-04 (−0.05)	−3.43e-04 (−0.05)
Metropolitan districts	−0.945 (−0.29)	0.042 (0.04)	−0.963 (−0.61)	−5.260 (−0.38)	−0.028 (−0.05)	−9.42e-05 (−0.05)	−7.67e-05 (−0.06)
Other urban LADs	−0.252 (−0.22)	−0.780 (−0.45)	−2.952 (−1.33)	−3.489 (−0.94)	−0.035 (−0.05)	−4.52e-04 (−0.05)	−7.98e-05 (−0.07)
Rural LADs	−2.029 (−0.35)	−1.512 (−1.13)	−2.221 (−0.47)	−2.143 (−0.45)	0.187 (0.05)	−4.95–04 (−0.05)	−8.74e-05 (−0.30)

direction, i.e. in the opposite direction in the two models. For example, when an adult joins a household, the likelihood of acquiring a car increases and when an adult leaves the household the likelihood of car disposal increases. The increase in the number of adults in the household may be associated with the offspring reaching their driving age and often having their own cars rather than sharing the existing family cars (Clark et al., 2016). These findings are consistent with the previous empirical works suggesting a positive relationship between the number of household cars and the number of adults in the household (Dargay and Vythoulkas, 1999; Mohammadian and Miller, 2003). Consistently, cohabitation formation increases the likelihood of an increase in the number of household cars simply because partners bring their cars with them when cohabitation is formed. This pattern also holds in the opposite scenario, where the dissolution of cohabitation leads to a reduction in the number of household cars. As the number of employed individuals in a household rises, the household becomes more likely to acquire a car and less inclined to dispose of one. This trend may be attributed to changes in both household income and mobility needs. Also, having a child increases the likelihood of acquiring a car which is logical as families may require a car to meet the changing activity patterns following the needs of a child. There is also evidence from the literature that new parents are more likely to purchase a car (Oakil et al., 2014) and less likely to use other modes but private cars (McCarthy et al., 2019).

The effect of change in employment status on the likelihood of increasing car numbers may be counterintuitive at first glance. However, acquiring an additional car following job loss could facilitate access to new employment opportunities. The effect of the vehicle price index was found statistically insignificant in both models. Lastly, the number of buses per 1000 people is statistically significant and negatively related to the probability of shedding a car. While this is counterintuitive, a similar finding was reported by Bilgin et al. (2023a), who observed that an increase in the number of buses per 1000 people causes vehicle ownership to increase at the LAD level in Great Britain. In future works, potential reasons for this relationship should be investigated in detail.

Residential environment types and residential relocation are found to have statistically insignificant effects on the decision to acquire a car. On the other hand, certain types of residential relocation have a statistically significant effect on the decision to dispose of a car one period later than when the relocation took place which may be expected as it takes time for households to realise and decide whether having a car or multiple cars is necessary or convenient. In particular, households moving from London to rural areas are less likely to dispose of a car. Also, the reduced likelihood of car disposal when moving within the same type of residential environment may be related to the desire for improving housing such as moving to a detached house or reducing housing costs by moving out of the city centre. These results may imply that households are less inclined to decrease the number of cars they own when they move from less car-dependent areas to more car-dependent areas.

5. Conclusions

Previous cross-sectional disaggregate studies regarding the effects of ridesourcing on car ownership have found that ridesourcing users tend to own no or fewer cars than non-users. However, it is unclear whether ridesourcing has caused them to reduce the number of cars they own or they use ridesourcing more frequently because they have no or an inadequate number of cars available in the household in the first place. Using 11 years of data from a large household longitudinal study representative of UK households, we provide better evidence about the potential causal impact of ridesourcing availability on the decision to change car ownership status, while controlling for the wide variety of life events, socio-economic and demographic characteristics and built environment characteristics.

Our findings suggest that, whilst ridesourcing has the potential to reduce the likelihood of car acquisition, it is not an effective motivator to shed a car at this stage – at least in the UK. It appears ridesourcing slows down the increase in car ownership in the UK by stopping UK households from acquiring a new car. However, it is not likely to reverse the current car ownership growth trend as ridesourcing has not caused UK households to shed their cars, at least in the current situation. Our results are in line with previous studies suggesting that ridesourcing itself is not a strong motivator to give up car ownership (Bekka et al., 2020). However, it may require a longer time to observe the genuine effect of ridesourcing on car ownership which is a long-term decision (Sabouri et al., 2020).

Our results confirm previous research by showing that changes in household composition (change in the number of adults and number of children, change in cohabitation status, having a child) have a potentially stronger impact than ridesourcing availability on both car acquisition and disposal decisions of UK households. Perhaps, households may own a single household car and use it occasionally for certain activities which are perceived as car-dependent regardless of all other factors mentioned here (Mattioli et al., 2016). Then, the ultimate goal should be encouraging people to use sustainable modes for their regular trips and supporting the public transit network by filling the temporal and spatial gaps.

The findings of this study offer several policy implications for transport authorities and decision-makers. First, the results of the heterogeneous car acquisition model suggest that under certain circumstances car ownership level may be lowered in the presence of ridesourcing. Particularly, ridesourcing has the potential to substitute for a second household car. From a planning and sustainability perspective, this suggests that ridesourcing could help reduce overall vehicle ownership, particularly in multi-vehicle households. This trend may offer additional potential sustainability benefits, such as lower parking demand, and decreased emissions, only when supported by policies that incentivise low-emission vehicles and shared trips given ridesourcing itself is a car-based mode.

From regulatory perspectives, ridesourcing regulations in the UK appear to mitigate excess car purchases by maintaining certain entry barriers into the taxi market (Bilgin et al., 2023b). However, our results reveal spatial heterogeneity, with differing effects across regions varying in urbanisation levels. This underscores the importance of location-specific regulatory approaches to better utilise the benefits of ridesourcing. For example, policies may need to differentiate between urban and rural contexts to help integrate with public transport in urban areas while improving overall accessibility in underserved rural areas with limited transport alternatives.

Our models also suggest that better accessibility of amenities along with more reliable and higher quality public transit services in urban areas could make private cars less of a necessity in the presence of ridesourcing. In that sense, it is important to improve the built environment based on the conventional factors of a car-independent environment (5Ds) (Ewing and Cervero, 2010), while working on effective integration of ridesourcing into existing transport systems where public transit services play a central role. Overall, transport policies aiming to reduce private car dependence could leverage this trend by promoting shared mobility options and integrating them with public transit services.

Lastly, although car ownership is a strong predictor of car use, there may be a divergence between car ownership and car use especially in the era of innovative on-demand mobility services like ridesourcing that provides non-car owners with access to private cars. Although the overall effect on traffic, transportation systems and the environment has yet to be fully discovered, there is evidence from the literature that ridesourcing has caused an increase in vehicle miles travelled mostly because of deadheading and induced travel demand (Henao and Marshall, 2018; Tengilimoglu and Wadud, 2022; Ward et al., 2019). Therefore, despite the potential positive impacts of ridesourcing on slowing down the increasing car ownership, the ultimate effort should focus on reducing car use. To achieve this, certain practices may be applied to discourage people from using personal cars, such as increasing the cost of car ownership and use and implementing restrictions on car use and parking which seems to prove its success in London (Bilgin et al., 2023a). Also, some actions may be introduced for more efficient and sustainable operation of ridesourcing vehicles such as supporting the electrification of ridesourcing vehicles and implementing curb space management practices to reduce empty miles (Tengilimoglu and Wadud, 2022). For example, the recent update to PHV licensing requirements in London requires that all PHVs being licensed for the first time by Transport for London (TfL) from 2023 onwards must be capable of zero emissions or comply with specific emission standards. Nevertheless, such practices should not be limited to London and should spread across the country. Finally, and more importantly, ridesourcing should be implemented as an effective connector to public transit services and the shared use of these services should be encouraged (Marsden et al., 2019).

This study contributes to the relevant literature by providing empirical evidence on the effect of ridesourcing on household car ownership in the UK where there was a lack of evidence. However, there are still some limitations. The availability of ridesourcing services was measured at the LAD level due to data availability. However, the service level of ridesourcing may not be homogeneous within LADs. Also, the adoption rate and frequency of ridesourcing use, which are shown to correlate with the number of household cars (Sabouri et al., 2020), may vary between individuals in LADs. Therefore, the results may not fully represent the causal relationship. In future studies, the effect of ridesourcing can be better represented using indicators such as adoption rate or use frequency.

CRediT authorship contribution statement

Pinar Bilgin: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Giulio Mattioli:** Writing – review & editing, Supervision. **Malcolm Morgan:** Writing – review & editing, Supervision. **Zia Wadud:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

A. Sample characteristics

Table A1 presents descriptive statistics for three samples: full sample with longitudinal weights provided by the data owner, subsample (sample with known ridesourcing variable) with data owner's longitudinal weights and subsample with final weights which are the combination of data owner's longitudinal weights and IPF weights.

Table A1
Descriptive statistics.

	Full sample with UKHLS weights		Subsample with UKHLS weights		Subsample with final weights	
	Mean / %	Std. dev.	Mean / %	Std. dev.	Mean / %	Std. dev.
Ridesourcing availability						
Available	–		58.78 %		49.88 %	
Not available	–		41.22 %		50.12 %	
Change in the number of household cars						
No change	80.88 %		83.65 %		81.37 %	
Decrease in the number of household cars	9.14 %		8.40 %		9.38 %	
Increase in the number of household cars	9.97 %		7.94 %		9.25 %	
Household car numbers (%)						
Zero car	17.27 %		28.56 %		20.04 %	
One car	37.72 %		41.66 %		40.61 %	
Two cars	32.45 %		23.48 %		30.07 %	
Three or more cars	12.55 %		6.31 %		9.29 %	
Residential environment						
Rural LADs	22.32 %		7.86 %		22.02 %	
Other urban LADs	49.02 %		31.94 %		48.74 %	
Other metropolitan districts	17.05 %		33.25 %		17.4 %	
London	11.61 %		26.95 %		11.83 %	
Residential relocation						
No relocation	92.64 %		91.51 %		90.75 %	
From rural LSOA to urban LSOA	0.53 %		0.42 %		0.74 %	
From rural LSOA to London	0.02 %		0.05 %		0.02 %	
From urban LSOA to rural LSOA	0.64 %		0.28 %		0.64 %	
From urban LSOA to London	0.11 %		0.28 %		0.19 %	
From London to rural LSOA	0.16 %		0.14 %		0.10 %	
From London to urban LSOA	0.05 %		0.02 %		0.02 %	
Within the same area group	5.86 %		7.31 %		7.54 %	
Age	46.68	17.96	50.28	16.39	47.42	0.43
Equivalised household income (1000)	1.72	2.24	1.66	2.17	1.63	0.02
Education level						
Tertiary education qualification	63.97 %		60.05 %		63.89 %	
No tertiary education qualification	36.03 %		39.95 %		36.11 %	
Number of kids in the household	0.55	0.94	0.52	0.91	0.57	0.03
Number of employed people in the household	1.41	1.41	1.18	1.00	1.34	0.02
Population density	1775.91	2384.31	3294.53	3175.91	1872.68	71.74
Job density	0.79	1.11	0.82	0.94	0.79	0.01
Number of buses per 1000 people	2.51	1.42	2.49	1.59	2.48	0.04
Rail transport availability						
Available	45.61 %		54.56 %		31.36 %	
Not available	54.39 %		45.44 %		68.64 %	
Vehicle price index	100.95	1.98	101.11	1.99	101.22	0.01
Change in the number of adults						
No change	87.07 %		86.73 %		85.59 %	
Adult joined	6.40 %		5.86 %		6.60 %	
Adult left	6.54 %		7.40 %		7.81 %	
Birth or adoption of a child						
Yes	3.25 %		2.94 %		3.45 %	
No	96.75 %		97.06 %		96.55 %	
Change in cohabitation status						
No change	96.75 %		96.35 %		95.89 %	
Cohabitation formed	1.89 %		1.83 %		2.23 %	
Cohabitation dissolved	1.37 %		1.83 %		1.87 %	
Change in employment status						
No change	89.76 %		90.85 %		90.32 %	
Employment gained	4.38 %		3.49 %		3.82 %	
Employment lost	3.91 %		3.69 %		4.06 %	
Became retired	1.96 %		1.97 %		1.80 %	

The chart in Fig. A1 displays the percentage of observations where households acquired a car during the analysis period. The blue bars represent the total observations of car acquisitions, while the purple line indicates observations where ridesourcing is available. Similarly, Fig. A2 shows the percentage of observations where households disposed of a car during the analysis period.

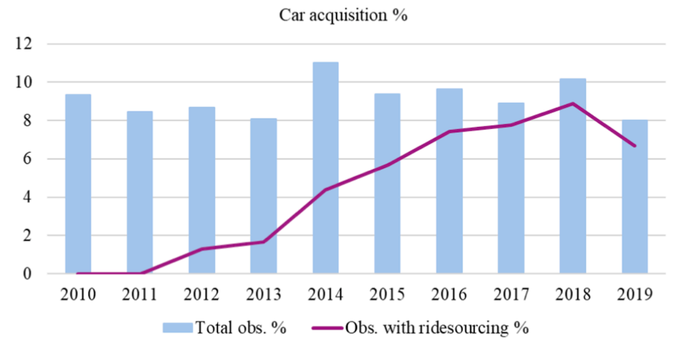

Fig. A1. The percentage of observations where households acquired a car

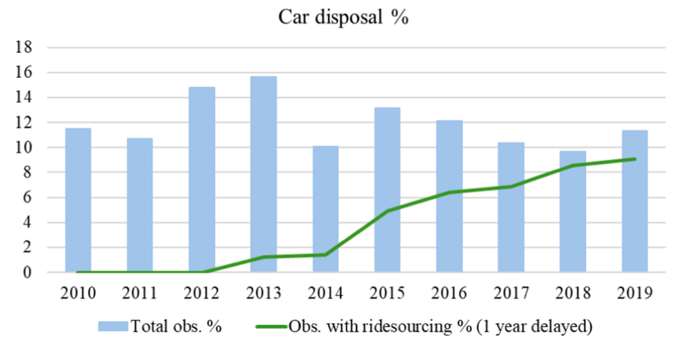

Fig. A2. The percentage of observations where households disposed of a car

Finally, Table A2 presents a cross-tabulation of some variables by car acquisition and car disposal in the final sample.

Table A2
. Cross tabulation by car acquisition and car disposal (subsample with final weights).

		Car acquisition = 1	Car disposal = 1
Ridesourcing availability			
	Available	4.06 %	4.48 %
	Not available	5.19 %	7.25 %
Number of household cars			
	Zero car	2.06 %	
	One car	4.01 %	2.28 %
	Two cars	1.86 %	4.33 %
	Three or more cars	0.82 %	3.48 %
Residential relocation			
	No relocation	7.87 %	9.09 %
	From rural to urban	0.94 %	0.33 %
	From urban to rural	0.19 %	0.02 %
	From urban to London	0.15 %	0.08 %
	From London to rural	0.25 %	0.03 %
	Within the same area group	1.05 %	2.09 %
Change in the number of adults			
	No change	6.9 %	6.55 %
	Adult joined	1.76 %	0.54 %
	Adult left	0.59 %	4.64 %
Having a child			
	No	8.77 %	11.22 %
	Yes	0.49 %	0.51 %
Change in cohabitation status			
	No change	8.14 %	10.50 %
	Cohabitation formed	1.01 %	0.33 %
	Cohabitation dissolved	0.10 %	0.91 %
Change in employment status			

(*continued on next page*)

Table A2 (*continued*)

	Car acquisition = 1	Car disposal = 1
No change	8.36 %	9.92 %
Employment gained	0.25 %	0.65 %
Employment lost	0.53 %	0.90 %
Became retired	0.11 %	0.27 %

B. Roboustness test using alternative ridesourcing variables

This section presents the estimates using alternative ridesourcing variables with 3-month, 6-month and 1-year buffers from the original ridesourcing entry date following the baseline specifications presented in Eqs. (1a) and (1b) for the car acquisition model and car disposal model, respectively.

In both models, estimated coefficients and marginal effects are consistent with overlapping estimates at 95 % CI.

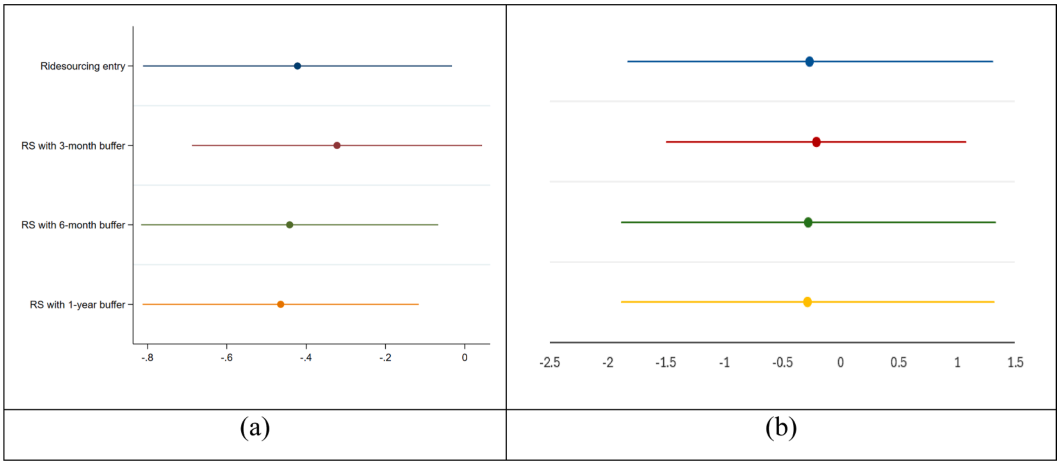

Fig. A3. Comparison of the (a) estimated coefficients and (b) marginal effects for the variable of interest with 3-month, 6-month and 1-year buffers from the car acquisition model

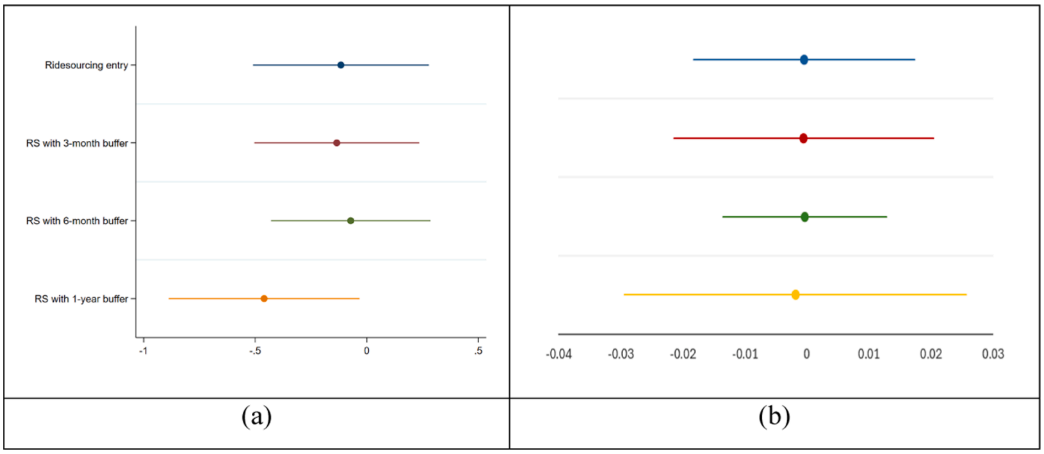

Fig. A4. Comparison of the (a) estimated coefficients and (b) marginal effects for the variable of interest with 3-month, 6-month and 1-year buffers from the car disposal model

C. Heterogeneous effect models

Table A3
. Confounding factors in car acquisition and car disposal based on the number of household cars and residential environment.

	Car acquisition model (ref: no car acquisition)		Car disposal model (ref: no car disposal)	
	OR	t-stat.	OR	t-stat.
Age	0.791	−0.97	0.736	−1.13
Age squared	0.997***	−5.04	1.005***	5.17
Equivalised household income (1000)	1.147*	1.72	0.940	−1.37
Equivalised household income squared	0.990**	−2.11	1.001	1.57
Education level (ref: No tertiary education qualification)	1.579	0.28	0.777	−0.30
Number of kids in the household	0.792	−1.28	1.055	0.34
Number of employed people in the household	3.121***	9.96	0.512***	−6.26
Population density (log)	0.374**	−2.02	0.986	−0.05
Job density (log)	1.008	0.01	0.755	−0.36
Number of buses per 1000 people	0.929	−0.69	0.790**	−2.06
Rail transport availability	1.056	0.09	0.101	−0.96
Vehicle price index	1.468	1.64	1.152	0.56
Residential relocation (ref: no relocation)				
From rural to urban	0.364	−1.15	0.799	−0.33
From urban to rural	2.231	1.30	12.156	1.54
From urban to London	0.146	−1.07	0.718	−0.30
From London to rural	5.450	1.24	4.61e-10***	−17.92
From London to urban	0.140	−1.38	–	
Within the same area group	1.162	0.48	0.567*	−1.77
Change in number of adults (ref: No change)				
Adult joined	1.434**	2.38	1.020	0.07
Adult left	1.269	0.85	6.231***	7.06
Birth or adoption of a child	2.348***	2.97	1.220	0.77
Change in cohabitation status (ref: No change)				
Cohabitation formed	2.395***	2.84	2.483	1.18
Cohabitation dissolved	1.012	0.04	2.069	1.50
Change in employment status (ref: No change)				
Employment gained	0.489	−1.34	1.469	1.32
Employment lost	1.989*	1.91	0.867	−0.48
Became retired	1.820	1.35	1.012	0.05
Year fixed effects	Yes		Yes	
Unweighted sample	46,954		38,798	
Weighted sample	5510.4		3908.9	
AIC	15566.5		8650.7	
BIC	16025.3		9015.4	
McFadden's pseudo R^2	0.38		0.48	

Data availability

The authors do not have permission to share data.

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