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The effects of ridesourcing services on vehicle ownership in large Indian cities

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ABSTRACT

The role of ridesourcing services on vehicle ownership is an important research area, especially in the context of the environmental implications and long term sustainability of these services. However, evidence from literature so far is mixed, with studies reporting both an increase and reduction in ownership, sometimes in the same country. This research adds to the current knowledge by econometrically estimating the impacts of ridesourcing services on vehicle ownership in a large emerging economy, India. Using a cross-sectional timeseries data on vehicle registrations in 18 large cities in India over 17 years, we find a statistically significant reduction in vehicle ownership (compared to baseline) since the introduction of these services. The growth in vehicle ownership has reduced by around 7.7% in the cities together since the introduction of ridesourcing services and this impact appears to grow over time; but the overall ownership is still increasing.

1. Introduction

Since their introduction nearly a decade ago, e-hailing or ride-sourcing services have rapidly become popular and have disrupted the way people travel – especially in the urban areas. These on-demand mobility services utilize information technology and smartphones to efficiently and reliably provide the service to the intending passengers (Shaheen et al., 2015). They are now available in almost all major cities in the world, whether in developed, developing or emerging economies. The services are provided by some large transport network companies (known as TNCs) such as Uber, Lyft, Ola, Grab, Bolt, Didi and other smaller local and regional providers. Although cars or four-wheeled vehicles are the most common form of transport used for ridesourcing services, motorcycles have also become quite popular in some developing and emerging countries – especially in South-East Asia and Sub-Saharan Africa (Wadud, 2020a).

Modelling the impacts of ridesourcing services on various transport and environmental outcome such as congestion (Li et al., 2017; Henao and Marshall, 2019; Erhardt et al., 2019), parking (Henao et al., 2018; Wadud, 2020b) or emissions (Ward et al., 2019) is an active area of research, Tirachini (2020) provides a recent review of existing studies. Vehicle ownership is another such metric, which can act as a marker for vehicle miles travelled, congestion or carbon emissions – all of which are relevant for transport planning. It is also argued – especially in the context of vehicle automation – that e-hailing services will reduce vehicle ownership in future, which makes ownership an important metric. Any such changes in ownership of vehicles also have a large impact on the vehicle manufacturing industry. However, research on the effects of ridesourcing services on vehicle ownership has so far provided mixed evidence: Ward et al. (2021), Guo et al. (2018, 2020), Gong et al. (2019) and Paundra et al. (2020) show an increase in ownership, while Ward et al. (2019) and Guo et al. (2020) report a reduction. These studies are also concentrated mostly in the US and China at the moment, with limited understanding of the potential impacts in other parts of the world. As such there is a need for further research in this area, and this paper investigates the vehicle ownership impacts of ridesourcing services in India.

This paper contributes to literature by providing new evidence from a new region that has so far been unexplored. India is an interesting country in this context for several reasons: it has a large population with a growing middle class resulting in one of the largest and fastest-growing vehicle markets in the world (Bajwa 2021) and rapidly increasing carbon emissions from the road transport sector (Climate Action Tracker 2020); it also has its own home-grown TNC, Ola, which started quite early, in 2010, which provides an opportunity to observe a long time-series of vehicle ownership post-TNC. Also, a longer time-series of

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aggregate vehicle holding data is utilized in this study, as compared to other studies.

The paper is laid out as follows. Section 2 describes the evolution of ridesourcing services in India, while section 3 reviews the econometric literature on the effects of these services on vehicle ownership. Sections 4 and 5 describe the data and methods respectively, while section 6 presents the results. Section 7 concludes.

2. Ridesourcing in India

India is the second largest country in the world, by population. Until recently it was one of the fastest growing economies as well, giving rise to a growing middle class with increasing demand for travel, and car travel, in particular. Since 1980 travel demand in the country has grown eight-fold and further growth is expected in future, driven by growth in population and income (Boston Consulting Group, 2018). It is already the fourth largest vehicle market in the world, and is expected to be among the top three markets by sales volume by 2026 (Bajwa, 2021). Indian cities are also growing rapidly, yet, there is a lack of good public transport and informal paratransit such as taxis and autorickshaws are popular modes of transport. The country also has a thriving and innovative information technology sector. This made India an ideal country for innovations in the transport services sector too.

The first ridesourcing operation in India can be traced back to a local company Ola starting its operations in Mumbai, the largest city in India, in December 2010 (Kumar, 2021). Like its TNC counterparts in other parts of the world, Ola then expanded rapidly through various cities in India. During the 2018–2019 financial year, Ola is reported to have offered around 28 Million rides per week (Singh, 2020). Ola's closest rival in the ridesourcing market in India is Uber, which first started its operations in San Francisco in the US in 2009 and entered India in 2013 as part of its global expansion strategy. Since then Uber has consistently increased its market share in India and by 2019 was reported to have served around 14 Million trips a week (Singh, 2020). Uber also claims to have more than 50% of Indian app-based ride services market (Singh, 2020), although it is difficult to establish or compare with the Ola statistics above as it is not known which services in their portfolio are reported. Ola operates in around 250 cities in India currently (Singh, 2020), while Uber operates in 89 (Poovanna, 2020). Together, these two TNCs have provided 2.2 Billion trips annually in India before the start of the COVID19 pandemic. One significant difference in the Indian ridesourcing market compared to that in the US is that a large share of Uber and Ola's driver-partners in India come from existing taxi-type services. Ola and Uber are often termed as taxi-aggregators in India.

Both Uber and Ola offer ridesplitting services or the shared-ride services UberPOOL and OlaShare in India. There have been other important innovations in India's ridehailing market too. A third major TNC, Rapido, started offering motorcycle based ride services in 2015 (Dutta, 2020). This was quickly copied by both Ola and Uber in 2016, although Rapido remains the market leader in the motorcycle ride segment, at least for the time being (Malvania, 2020). Beyond cars and motorcycles, the app-based service concept has now been extended to three-wheeler auto-rickshaws, with Ola, Uber and Jugnoo the major players in this market. Despite some initial hiccups – especially, widely publicized concerns about women's safety in TNC vehicles – app-based ride services have expanded rapidly in India in the past decade. Ease of travel (comfortable, hassle-free), low fares, unavailability (and poor quality) of public transport and lack of parking availability are mentioned as the reasons for the popularity of the ride services (Mulukutla, 2016). The Government of India considers app-based ride services as a significant component in its shared mobility strategy to reduce congestion and fuel consumption and to improve air quality (NITI Aayog et al., 2018).

While there are a few studies that investigate the user characteristics and motivations for using TNC services in India, e.g. Malik et al. (2020), the number of studies on the impacts of these services on transport outcome is very limited. Of these, Agarwal et al. (2021) have reported an increase in congestion in Delhi and Mumbai due to the ridesourcing services. On the other hand, a recent global survey indicated that Indian consumers are more willing than those in other countries to forego car ownership if good quality ridesourcing services are available (Deloitte, 2020). However, there are no studies known to us that investigated the effects of these services on actual vehicle ownership or sales in India.

3. Effects of ridesourcing on vehicle ownership

There are two sets of possibilities about the effects of ridesourcing services on vehicle ownership. The first hypothesizes that the ridesourcing services are the closest possible commercial alternative to privately owned vehicles, providing point-to-point services at a reasonable wait time, cost and reliability. As such people can switch from owning a vehicle exclusively to using these 'shared vehicle' services and reduce private ownership of vehicles. The immense growth in the 'shared economy' services (TNCs, AirBnB, WeWork, etc.) during the past decade points to this possibility. This hypothesis will likely be valid in places with high vehicle ownership and low public transport share, low regulation for operations of ridesourcing services and high regulation (resulting in high costs and fares) for traditional taxis. This effect is sometimes referred to as the cannibalization effect in the sharing economy literature (Paundra et al., 2020).

It is also possible, in a different context, for ridesourcing services to increase the number of vehicles. In regions or cities that enjoy a large public transport modal share, ridehailing services can encourage a modal switch away from public transport modes – even a small such switch can require a substantial increase in the demand for ridesourcing vehicles and as such total vehicle ownership. More importantly, the online platforms of the TNCs allow vehicle owners to profit from the excess capacity in vehicles when not in use, and thus increase the value proposition for owning vehicles – especially for 'marginal' owners. Both of these could increase vehicle ownership. This effect is known as the value enhancement effect (Paundra et al., 2020).

Determining the net effects of these opposing impacts is a matter of empirical investigation, and there are two different strands of literature that attempted to answer this question. The first utilizes primary data from questionnaire surveys. Although the exact questions can vary between studies, broadly speaking, these studies ask the respondents about their vehicle ownership or intentions to own (or give-up) vehicles and correlates it with their use of or availability of ridesourcing services. Majority of these studies (Clewlow and Mishra, 2017, Hampshire et al., 2018) are conducted in the US, use primary survey data and point to a reduction (or intended reduction) in at least some household's vehicle ownership that can be attributed to the introduction of ridesourcing services. This literature often do not investigate the supply side, i.e. the purchase of new vehicles as a potential income source via the ridesourcing services. Following a different approach, but still using disaggregate data at the household level, Sabouri et al. (2020) report a statistically significant negative relationship of car ownership with the number of years of Uber operation in a county in the US. We do not critique this literature further here as our focus is on the studies that use aggregate vehicle registration or sales data, which is the second approach to quantify the effects.

The econometric evidence using actual aggregated vehicle registration or sales data is mixed so far (Table 1). Ward et al. (2019) report that the introduction of Uber has reduced vehicle ownership in US states. However, Ward et al. (2021) later report the opposite findings for urban areas in the US, especially those areas with below-average car ownership. Previous non-econometric work on large urban areas in the US also appears to suggest the same (Schaller, 2019). Similarly, Wadud (2020a) reports an increase in motorcycle ownership in Dhaka, the capital of Bangladesh, since the introduction of motorcycle-based ride services in the city. All of these studies investigate vehicle stock or ownership. On the other hand, Guo et al. (2020) focus on new vehicle sales data and

Table 1
Results of econometric studies on the effects of ridesourcing services on vehicle ownership.

Study	Year	Geography	Data type	Method	Conclusions
Gong et al.	2019	China	Panel/city	DiD	*New* registrations went up
Guo et al.	2018	China	Panel/city	DiD	*New* vehicle sales went up
Guo et al.	2020	China	Panel/province	DiD	*New* vehicle sales went up, weak evidence (at 90% confidence level)
		USA	Panel/state	DiD	*New* vehicle sales went down
Ward et al.	2019	USA	Panel/state	DiD	Ownership went down in states
Ward et al.	2021	USA	Panel/zipcode	DiD	Ownership went up in urban areas
Paundra et al.	2020	Indonesia	Panel/province	DiD	*New* vehicle registrations went up
Wadud	2020	Bangladesh	Timeseries/city	Intervention analysis	Motorcycle ownership went up

report a reduction in sales in the US since the entry of ridesourcing services. The findings on China are more consistent: all three studies (Gong et al. 2019; Guo et al. 2018, 2020) agree that new vehicle registrations or sales had increased in China since the introduction of Didi or Uber services. Similar increases in new vehicle registration was observed in Indonesia too (Paundra et al., 2020). In the global context, the mixed evidence base reveals that the impacts are likely location specific, and shows the need for gathering further evidence from other parts of the world, beyond the US, China and Indonesia only.

Nearly all of the aforementioned econometric studies utilize secondary panel data (cross-sectional units observed over different time periods either side of the intervention) and employ the difference-in-difference (DiD) technique to decipher the effects. Only Wadud (2020a) uses timerseries data for a city (and the rest of the country as counterfactual) and employs segmented regression (Lagarde, 2012) and intervention analysis techniques (Bernal et al., 2017). Some studies (Ward, 2019, 2020; Wadud 2020a) utilize vehicle registration or ownership data, whereas all three Chinese and the Indonesian studies use new vehicle sales or new registration data. Data can also be at different geographic levels: zipcode (Ward et al., 2021), city (Gong et al., 2019; Guo et al., 2018; Wadud, 2020a) or state or province (Ward et al., 2019; Guo et al., 2020; Paundra et al., 2020).

4. Data

Data availability and quality in developing countries like India is a major concern, especially for research using time series data. Vehicle category-wise registration data are available for 23 of the largest cities in India from the Ministry of Road Transport and Highways (2017) and Open Government Data (2020) for a reasonable timeframe (since 2001). These cities each had a population of at least 1.5 Million in 2017 and range from the megacities of Delhi and Mumbai to the (relatively) smaller Varanasi and Madurai. Although new cities entered this database as they grew larger over time, data for those cities are available for fewer years. The supposedly good quality data for these largest cities still appear fraught with challenges upon closer inspection. For example, the taxi registration statistics is not consistent across all cities. Some states (and as such cities in those states) have ridesourcing vehicles classified as taxis, while others have them within privately owned cars or jeeps (SUVs) category. As such we cannot separate these together and focus on combining taxis, cars and jeeps (SUVs) together to calculate total four-wheeled small passenger vehicles.

Converting the total of car, jeep and taxi registration data to vehicles per thousand population and plotting the series against time for each of the 23 cities clearly reveals further discrepancies, which need to be sorted (see Fig. 1). For cities where the discrepancies occur before year 2010, this is controlled by incorporating dummy variables for that city and for that time period. This approach is problematic for multi-period discrepancies during the later years, especially after ridesourcing services are introduced, given there is no way of knowing if the apparent discrepancy of the data is a genuine response to ridesourcing services or a simple data error or discrepancy. As such, we remove three cities Hyderabad, Pune and Surat from our analysis, although we do keep Vadodara which clearly has one large outlier in 2017 (4 years after the introduction of ridesourcing services, so unlikely to be a result of these services and more likely to be an error), which can be tackled via a dummy variable. A dummy variable is added for Visakhapatnam from 2014 to account for any disruption in the timeseries as it became the largest city of the new Andhra Pradesh after the partition of the original Andhra Pradesh. Delhi presents a challenge due to its earlier discrepancy in 2005–2006 data, but also because the ridesourcing services were banned there for 2 years in 2014–2015 due to safety concerns; this prompts the removal of Delhi too. Kolkata, another megacity, also shows quite unusual patterns of vehicle registration data, so it is removed from the analysis too. As such we conduct the analysis on the remaining 18 cities: Ahmedabad, Bangalore, Bhopal, Chennai, Coimbatore, Indore, Jaipur, Kanpur, Kochi, Lucknow, Ludhiana, Madurai, Mumbai, Nagpur, Patna, Vadodara, Varanasi and Visakhapatnam. The introduction year of the ridesourcing services in these cities are found from various news articles on the internet.

City specific income data are not available, so state GDP per capita (Reserve Bank of India, 2020) are used instead, in real terms. Although fuel prices (Pattabiraman, 2018) and vehicle price indices (Office of the Economic Adviser, 2020) over time were collected, these values are for the whole country and as such becomes collinear with the yearly fixed effects in the model (see methods) and was utilised only in those models that did not have yearly fixed effects. Figs. 1 and 2 present the evolution of vehicle per capita and real GDP per capita in the 18 cities.

5. Methods

Our dataset is panel or timeseries-cross-sectional since it follows 18 large Indian cities over 17 years. However, unlike typical panels or models that use difference-in-difference technique, the time dimension is substantial in our dataset (the longest timeseries so far was used by Ward et al., 2019, 11 years, which was substantially smaller than their cross-sectional units, 50 US states). We are also interested in the changes in the temporal dimension, i.e. changes within each city over time, which lends itself to a fixed effects panel type regression. Adding yearly fixed effects to city fixed effects results in the difference-in-difference technique (Arnold, 2018) that has been extensively used in literature to understand the causal effects of external events or interventions.

FE panel regression parameters can be correctly and efficiently estimated using Ordinary Least Squares (OLS) as long as the errors are well-behaved (homoscedastic, independent). However, if the errors are not well-behaved, the standard errors from OLS or FE panel estimation can be incorrect, leading to erroneous inferences. There is always the possibility that, in real-world dataset(s), the errors are neither homoscedastic nor independent. For example, the errors can be contemporaneously correlated as large errors at one time for one city could be correlated with the errors of other cities at the same time – this can result from not including a variable that may have affected all observations at the same time (say, a nationwide policy change). Temporal dependence

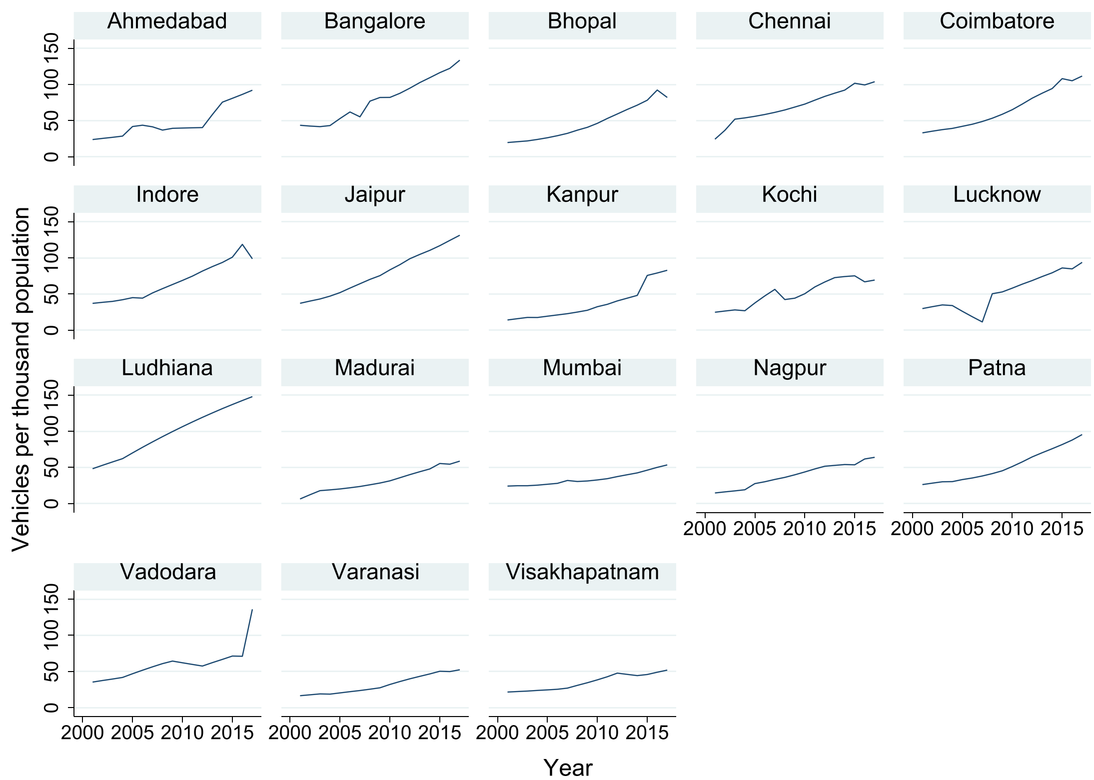

Fig. 1. Evolution of vehicles ownership in 18 cities in India.

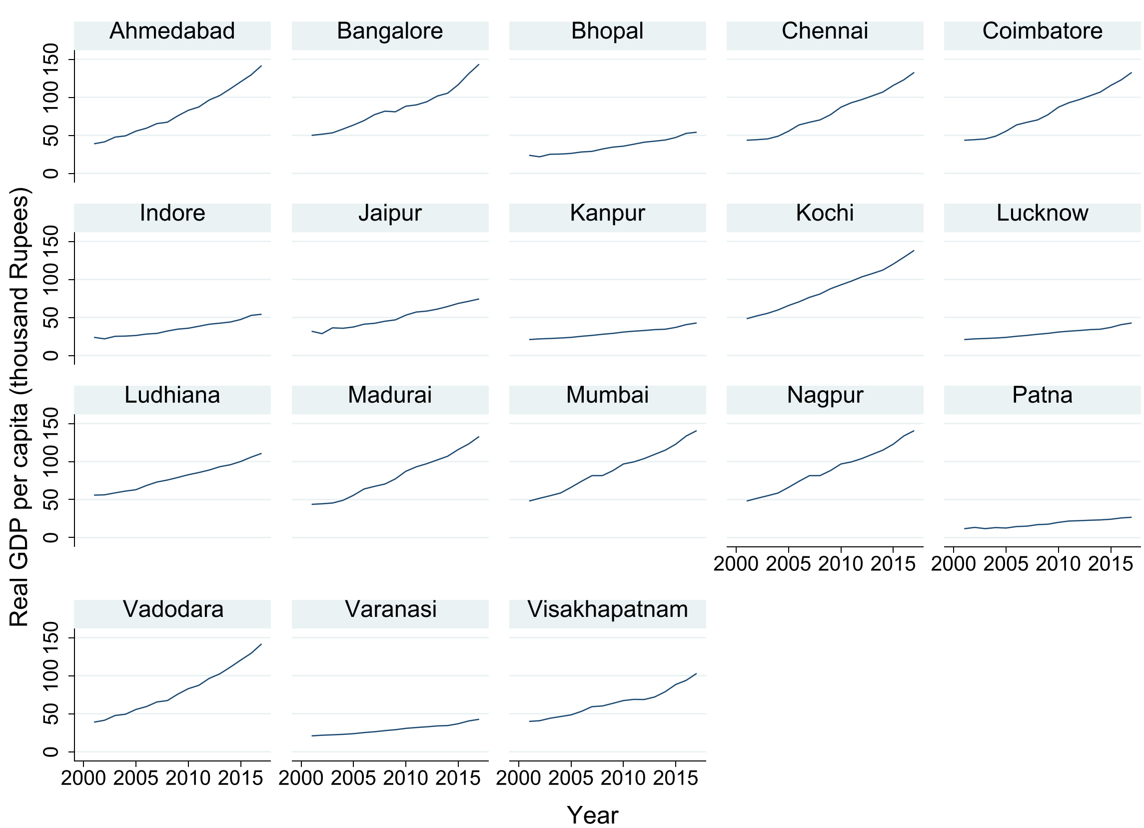

Fig. 2. Evolution of real GDP per capita.

of errors (serial correlation) within the same city is also possible for time-series data, especially if the time dimension is significant as in here. Due to the very different sizes of the cities in the dataset, it is also possible for the variances of the errors to differ between cities, showing heteroscedasticity, instead of homoscedasticity as required by the assumptions of OLS. All three violations to the assumptions of an OLS estimation are possible in our dataset.

Feasible Generalised Least Squares (FGLS, Parks, 1967) can be used to correct for these limitations. However, Beck and Katz (1995a, 1995b) and Beck (2001) compared several methods (including FGLS) to strongly suggest the use of 'panel corrected standard errors (PCSE)' on OLS estimates in order to get correct inferences for panel data when the time dimension is *not* negligible. Specifically, they showed that using the typical FE OLS estimate or FGLS estimate produce overly optimistic standard errors especially in cases where the number of cross-sectional units are between 10 and 20 and the number of temporal units are between 10 and 40, which is our case. Such dataset with relatively larger temporal observations compared to cross-section is sometimes known as timeseries-cross-section (TSCS) instead of panel, which deals with a large number of cross-sections observed over a relatively smaller timescale. As such, the PCSE technique is followed in this research. The longer time dimension also requires additional tests with regards to the presence of serial correlation in the errors. A typical DiD estimation, however, do not consider these additional issues in relation to TSCS data.

Our econometric model follows the specification below:

$$VPC_{it} = \alpha_i + \beta_t + \delta_j X_{jit} + \gamma DRS_{it} + \theta_k D_{kit} \quad (1)$$

where, VPC_{it} = vehicles per thousand people in city i in year t - in logarithm.

X_{jit} = j-th explanatory variable (continuous) in city i in year t - in logarithm.

D_{kit} = k-th dummy variable for data discrepancies or specific events in city i in year t.

DRS_{it} = dummy variable (=1) if ridesourcing service is available in city i in year t.

The Greek letters represent the parameters to be estimated. α_i are the city-fixed effects whereas β_t are temporal fixed effects. θ_k represent the effects of specific events or data discrepancies. Eq. (1) represents a typical DiD or dummy variable specification (Models 1–2 below), where the parameter γ reveals the average effects of ridesourcing services on vehicle ownership. It is quite possible that the impact (if any) may grow over time. As such in some model specifications, the number of years since the introduction of the ridesourcing services (*RSYear*) is included instead of *DRS* to capture the effect (Models 3–4). This assumes a linear effect on ownership over time. In some specifications, the temporal fixed effects (β_t) are replaced by a common time trend (Models 5–6).

The key determinant of motor vehicle ownership over time – especially in a developing or emerging country – is income, often proxied by GDP per capita. Income determines the ability of the people to afford a personal vehicle and has been the major explanatory factor in the growth of vehicle ownership in many econometric studies, e.g. Dargay et al. (2007) or Chamon et al. (2008). Affordability and demand for vehicles are also determined by prices, so vehicle price indices and real fuel prices are also important explanatory factors.

The explanatory factors considered for the model are real GDP per capita and its square (to test for saturation effects of income), real fuel price, real vehicle price index (proxied by transport cost index) – all in logarithms. Also included are dummies for the introduction of metro services in a city (Mumbai, D-Metro introduction) and partition of states (e.g. Andhra Pradesh into Andhra Pradesh and Telengana, for Visakhapatnam, D-Visakhapatnam). As mentioned in the data section, there are some clear discrepancies in data for some periods; additional dummy variables for these specific cities and relevant time periods were introduced to control for these, these are D-Bangalore-07 for Bangalore in 2007, D-Kochi-0607 for Kochi in 2006/07, D-Lucknow-0607 for Lucknow in 2006/07, D-Vadodara-17 for Vadodara in 2017.

6. Results

Table 2 presents the results of the econometric models for vehicle ownership per capita for various specifications and estimation methods. The city and year fixed effects (when used) are suppressed, but linear trend effects (when used) are presented. Model 1 is the typical DiD model, with both yearly and city-specific effects. Model 2 is the same specification, but uses panel corrected standard errors (PCSE), corrections made for heteroscedasticity and contemporaneous correlation among errors. Models 3 and 4 are similar to 1 and 2 respectively, but instead of *DRS*, *RSYear* is used to capture the gradual effects of the ridesourcing services. Models 5 and 6 use a linear time trend (instead of yearly fixed effects) and *RSYear* (instead of *DRS*). Model 5 is estimated using panel fixed effects, while Model 6 uses PCSE, with corrections for both heteroscedasticity and contemporaneous correlation. Specification tests have shown the presence of heteroscedasticity and contemporaneous correlation of errors, but no serial correlation. This justifies the use of PCSE models (Models 2, 4 and 6) ahead of the typical FE or DiD models. While the model fit statistics (adjusted R^2) are nearly similar among these three models, Model 6 – the one without the yearly fixed effects – performs marginally better than the other two.

Our key parameter of interest is the dummy for the introduction of ridehailing services, *DRS* or year since the introduction of TNC services, *RSYear*. The parameter estimates for *DRS* or *RSYear* are negative and statistically significant at 95% confidence level across all three PCSE model specifications (Models 2, 4 and 6). This indicates that the vehicle ownership in India had likely decreased (compared to the baseline) since the introduction of the TNC services. The finding is robust across other model specifications too, including the simple DiD specification (Model 1). Both Models 1 (DiD) and 2 (FE with PCSE), which can directly estimate the average increase or decrease after the introduction of ridesourcing services, show that vehicle ownership in the cities considered had slowed down by around 7.7% ($e^{-0.080}-1$). It is important to note that this reduction is relative to the baseline vehicle numbers, which is growing, and *not* an absolute reduction in numbers. The slightly larger adjusted R^2 of Model 6 compared to others shows that the use of linear time and *RSYear* explains the data marginally better compared to the models with time fixed effects. This indicates that effects of the introduction of ridesourcing services were gradual and the total effects were increasing over time. This is, of course, expected since travel behaviour takes time to adjust.

Parameter estimates for other explanatory factors, when included, reveal expected results. Income has a statistically significant and positive effect on vehicle ownership, as is well-established for developing and emerging countries (Dargay and Vythoulkas, 1999). This effect declines at higher income, suggesting satiation – another finding which is fairly accepted in literature (Dargay and Vythoulkas, 1999). For the models without yearly fixed effects, fuel price and vehicle price index were statistically insignificant. In developing and emerging countries, vehicles are generally owned by the wealthier segment of the population, who are possibly not as sensitive to variations in fuel prices. Vehicle price index is decreasing consistently over time, making it correlated with linear year. For the model with yearly fixed effects, these two variables are dropped as they become perfectly collinear with yearly fixed effects.

Our findings for India are opposite to those found in the literature for China, another large emerging country, where *new* vehicle registration or sales have increased substantially since the arrival of local TNC, Didi, as highlighted earlier. China and India are, of course, very different countries, with different types of economic, social, urban and transport organizations; China also has substantially higher per capita income (nearly five times) and vehicle ownership (nearly three times) – all of these could have a role for the differences in the impacts in these two countries. Another important reason for the opposite findings is likely

Table 2
Econometric estimation results.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	FE	PCSE	FE	PCSE	FE	PCSE
Ln GDP per capita	1.803**	1.803***	1.573*	1.573**	1.380*	1.380*
Ln GDP per capita squared	−0.082**	−0.082***	−0.072**	−0.072**	−0.065**	−0.065**
Ln fuel price					−0.039	−0.039
Ln vehicle price index					0.276	0.276
DRS	−0.080*	−0.080**				
RSYear			−0.034**	−0.034**	−0.026*	−0.026**
D-Metro introduction	−0.137***	−0.137***	−0.103**	−0.103***	−0.099**	−0.099***
D-Visakhapatnam (Andhra partition)	−0.250***	−0.250***	−0.260***	−0.260***	−0.241***	−0.241***
D-Bangalore-07	−0.140	−0.140*	−0.148	−0.148**	−0.151	−0.151**
D-Kochi-0607	0.292***	0.292***	0.296***	0.296***	0.306***	0.306***
D-Lucknow-0607	−1.068***	−1.068***	−1.067***	−1.067***	−1.058***	−1.058***
D-Vadodara-17	0.286**	0.286	0.293**	0.293	0.304**	0.304*
Year linear					0.095***	0.095***
Year FE (β)	Yes	Yes	Yes	Yes	No	No
City FE (α)	Yes	Yes	Yes	Yes	Yes	Yes
Heteroscedastic error	No	Yes	No	Yes	No	Yes
Cross-correlated error	No	Yes	No	Yes	No	Yes
Autocorrelated error	No	No	No	No	No	No
Adjusted R^2	0.9242	0.9473	0.9244	0.9474	0.9229	0.9489
Observations	306	306	306	306	306	306

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

the differences in the vehicle ownership regulations in the two countries. In many of the largest Chinese cities (e.g in Shanghai, Beijing, Guangzhou, Tianjin, Shenzhen, Hangzhou), where ridesourcing is generally popular, there are restrictions on private vehicle ownership or private vehicle use. These restrictions keep private vehicle ownership artificially suppressed and potentially increase the demand for car-based ridesourcing services further, which operates within more favourable ownership conditions. Especially, electric vehicles benefit from a nationwide subsidy scheme, which makes the economics more favourable toward ridesourcing use (higher usage of ridesourcing vehicles allows a quicker recoup of the higher capital costs compared to private vehicles). On top of it, electric vehicles are either exempt from the registration caps or enjoy relaxed caps (in Beijing). Both of these factors – suppressed demand for car travel being met by ridesourcing services and favourable electric vehicle conditions for ridesourcing vehicles – likely led to an overall increase in new vehicle sales in China. On the other hand, Indian cities did not have such restrictions on vehicle ownership in place. As such, there was no artificially suppressed demand for car ownership and use that needed to be met by ridesourcing services (which could have substantially increased vehicle ownership). A larger share of Indian consumers are also willing to consider giving up vehicle ownership if good ridesourcing services are made available, as compared to Chinese consumers (Deloitte, 2020), indicating a consumer attitude away from vehicle ownership in India.

7. Conclusions

Our results show that the growth in vehicle numbers in the largest Indian cities have reduced slightly due to the introduction of the ridesourcing services. This indicates that the substitution away from ownership to mobility services (cannibalization effect) likely dominates over the attractiveness of vehicle ownership for income-generation opportunities (value enhancement effects) at an aggregate scale. This finding is somewhat supported by global consumer studies, which show that the share of people who question the need for owning vehicles in the presence of good ridesourcing services is the largest in India (Deloitte, 2020). It is important to note that our finding is for the overall impact in the cities considered, and there could well be some heterogeneity in the impacts in different cities. It will be useful to understand the impacts on different groups of similar cities or individual cities in future, however lack of good data remains a significant hurdle. Because of the heterogeneity the results may not be generalized to other smaller sized cities with lower car ownership, where value enhancement effects may still govern.

The wider societal implications of our findings are more nuanced. Although there is evidence that the ridesourcing services had a statistically negative impact on vehicle ownership, this finding is relative to the baseline of an already growing ownership. So, these services have merely slowed the rate of growth in ownership in Indian cities and the absolute number of vehicles will likely continue to grow as a result of increasing income and population. Still, for the automotive business sector, our results show a potential slowdown of the market compared to the rapid growth in the past two decades.

There are energy and carbon implications too. Given the inefficiency of ridehailing services (almost around 50% of the miles are empty miles/deadheading without any passengers, Tengilimoglu and Wadud, 2021; Wenzel et al., 2019), a slowdown in vehicle ownership does not necessarily result in a reduction in traffic congestion or air pollution. Indeed, Ward et al. (2019) could not find any statistically significant decline in travel distances, petrol consumption or air pollutants, despite reporting a reduction in ownership in the US. As such, ridesourcing services alone will not resolve the chronic congestion in many large Indian cities or reduce emissions of greenhouse gases and local air pollutants by themselves; and policies and regulations to address these challenges still need to be implemented.

There are causes for hope in the long run, though. Results show that the effects of ridesourcing services on ownership grow over time as more and more people shed vehicles or forego vehicle purchase. The potential reduction in the costs of automated ridesourcing services (Wadud and Mattioli, 2021; Bosch et al., 2018) may make these services even more attractive in future, reducing ownership even further. Investments in public transport infrastructure such as Mass Rapid Transit (rail based) and Bus Rapid Transit (BRT) is increasing in India. It is therefore possible that India may not experience the same vehicle growth trajectory as other industrialized countries, and ownership could stabilize at a smaller level if appropriate policies are implemented.

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.

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Author contributions

ZW conceived the research, conducted the final analysis and led writing. JN collected data, conducted preliminary analysis, searched literature and contributed to writing.

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