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Automobiles and urban density

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Abstract

How has the rise of the automobile influenced urban areas over the past century? In this paper, we investigate the long-run impact of car ownership on urban population density, based on a sample of 232 city observations in 57 countries. Using the presence of a domestic car manufacturer in 1920 as a source of exogenous variation, our IV estimates indicate that car ownership substantially reduces density. A one standard deviation increase in car ownership rates causes a reduction in population density of around 35%. For employment density, we find almost identical results. This result has important implications for vehicle taxation, car ownership growth in developing countries, and new transport technologies such as automated vehicles.

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1. Introduction

"We shall solve the City Problem by leaving the City."
—Henry Ford (1922), *Ford Ideals.*

A defining feature of urbanisation in the 20th century has been the introduction and rapid, wide-scale adoption of the automobile. By lowering marginal transport costs and eliminating the need to walk almost entirely, cars allow people to travel longer distances with greater flexibility in terms of routes and schedules. As Henry Ford predicted, this facilitated the decentralisation of cities via the outwards expansion of people and firms into the periphery where land is cheaper, thereby radically changing urban form (Anas et al., 1998; Baum-Snow, 2007; Baum-Snow et al., 2017).

Urban population density is perhaps the most distinguishing characteristic of a city and is a common measure of urban form. Higher density is associated with positive agglomeration economies, public transport efficiency and urban amenities (see Ciccone and Hall, 1996; Glaeser et al., 2001, 2008; Rosenthal and Strange, 2004), while lower density is linked with higher pollution levels, environmental damage and segregation of rich and poor (see Brownstone and Golob, 2009; Zhao and Kaestner, 2010; Couture et al., 2019; Gaigné et al., 2020). Studying the effect of automobiles on urban density is important as in most countries cars are subsidised, implying that car ownership is too high and therefore urban densities may be too low from a welfare perspective (Au and Henderson, 2006; Parry et al., 2007; Brueckner and Helsley, 2011). For example, in Europe, about 40% of all new cars are subsidised through distortionary company car taxation (Van Ommeren and Wentink, 2012), whereas congestion, safety and environmental externalities are only partially included in the overall price of car use in the US (Parry and Small, 2005).

The monocentric city model predicts that in cities where cars are cheaper, and therefore car ownership is higher, travel costs per unit of distance are lower and therefore it becomes more attractive to commute longer distances. This results in cities that are less dense in terms of population (Glaeser, 2008). Despite this topic's relevance and clear theoretical mechanism, Glaeser and Kahn (2004) argue that we know very little about the magnitude of the long-run effect of car ownership on urban density.

This knowledge gap is likely related to the econometric challenge for causal inference and the lack of a consistent dataset on urban and transport indicators. The first challenge is reverse causality: residents are more likely to use a car in cities with lower urban densities; therefore, car ownership rates in these cities may be higher (Bento et al., 2005; Duranton and Turner, 2018; Ewing et al., 2018). Hence, one may overestimate the causal (negative) effect of cars on density if reverse causality is ignored. The second challenge is that urban density is highly persistent over time and is correlated to many difficult-to-observe factors (e.g. land-use planning). So, in order to identify the causal long-run effect of cars on urban density, one requires a *long-term* exogenous shock in car ownership.

We address these challenges using an IV strategy and by leveraging the best available global dataset of large cities constructed primarily by Kenworthy and co-authors over various waves (Ingram and Liu, 1999; Kenworthy and Laube, 2001; UITP, 2015). As an instrument, we use the presence of a domestic car manufacturer in 1920, hence when few people owned cars. We provide evidence that countries with historic car manufacturers currently still pay lower prices for car use and ownership through lower taxation and more roads. Furthermore, we will show that the presence of a domestic car manufacturer in 1920 is uncorrelated to urban density around that time, which supports our argument that historic car manufacturers are a plausible instrument for car ownership.[1]

Our research design is inspired by Glaeser and Kahn (2004) who were, to our knowledge, the first (and only) to study the causal effect of car ownership on urban density. Using legal origin as an instrument for car ownership, they conclude that cities with lower car ownership rates tend to have higher urban densities. Their main estimate indicates that one additional car per 100 inhabitants is associated with a reduction in urban density of 7.2%. However, as the authors acknowledge themselves, given their limited dataset and identification strategy, these results should be interpreted as suggestive. Glaeser and Kahn (2004) employ data from Ingram and Liu (1999), which contains 70 observations for 35 cities in 18 countries (in 1960 and 1980). Our main contribution is to improve their analysis by expanding the dataset considerably, introducing a new identification approach and performing a more extensive set of robustness checks. Although we have observations for several periods for some cities, we treat the data as a cross-section and apply our main

1 Up to the extent that one is still concerned that omitted variables bias is an issue, we also estimate fixed-effects models and use the methodology proposed in Oster (2019) to show that our baseline OLS and IV estimates are conservative.

identification strategy for 232 city observations in 123 cities and 57 countries between 1960 and 2012.

Our work is closely related to a large literature studying the effects of transport infrastructure on the spatial distribution of people and jobs (Baum-Snow, 2007, 2010; Garcia-López et al., 2015; Baum-Snow et al., 2017; Levkovich et al., 2019; Heblich et al., 2020; Gonzalez-Navarro and Turner, 2018). This literature demonstrates that highways are an important driver of decentralisation in the 20th century, while subways only had a moderate impact. However, highways explain only a portion of car-induced decentralisation (for evidence, see Online Appendix B.4).

Various other policies, such as vehicle taxes, fuel taxes and parking regimes, affect car ownership and use and thereby urban density. Therefore, estimates of the effect of highways only give a partial view (e.g. in Norway, there are few highways while car ownership is high). Hence, we aim to obtain insight into the overall effect of the automobile, captured by a comprehensive measure such as car ownership, which is the focus of this paper.

The results indicate that one additional car per 100 inhabitants reduces population and employment density by around 2.2% in the long run. This effect appears to be mainly driven by expansions in the built-up area and not by population leaving the city, suggesting that cars facilitate low-density urban development in the periphery. We use these estimates to gauge the potential effects of growing car ownership rates in developing countries and the introduction of automated vehicles (AVs). Applying these estimates, for example, to developing Asian cities indicates that if car ownership increases to similar rates as seen in high-income countries, urban density may fall by over 50% in the long run. Our estimates are also relevant for high-income countries with low car ownership rates (e.g. Denmark) as AVs will likely increase access to cars and thereby, in the absence of policy, cause cities to decentralise.

The paper proceeds as follows. In Section 2, we introduce the data and provide some descriptives. In Section 3, we elaborate on the methodology. We report the main results and discuss some implications in Section 4 and Section 5 concludes.

2. Data and descriptives

2.1. Data

We use several sources of information. The most important source is city-level data on population, employment, area size, income and transportation, between 1960 and 2012. We obtain data for 1960 and 1980 from Ingram and Liu (1999), which comprises 70 from 35 cities in 18 countries. Data for 1995 come from the Millennium Cities Database (henceforth, MCD1995) and contain information on 100 cities from 51 countries (Kenworthy and Laube, 2001; Kenworthy, 2017). Finally, we also obtain data for 2012 from the Mobility in Cities database (henceforth, MCD2012), collected by UITP (2015). They use the same methodology as MCD1995, but instead include 63 cities from 39 countries (Figure 1). Some data points were missing in the original data, so we impute these observations using the most reliable data available as documented in Online Appendix A.1.

A key advantage of these sources is that they rely on a consistent methodology for data collection, which allows us to make accurate comparisons between cities from different countries and time periods. Most importantly, the metropolitan area is consistently defined as the ‘commuter belt or labour market region’ for all our data and hence captures the

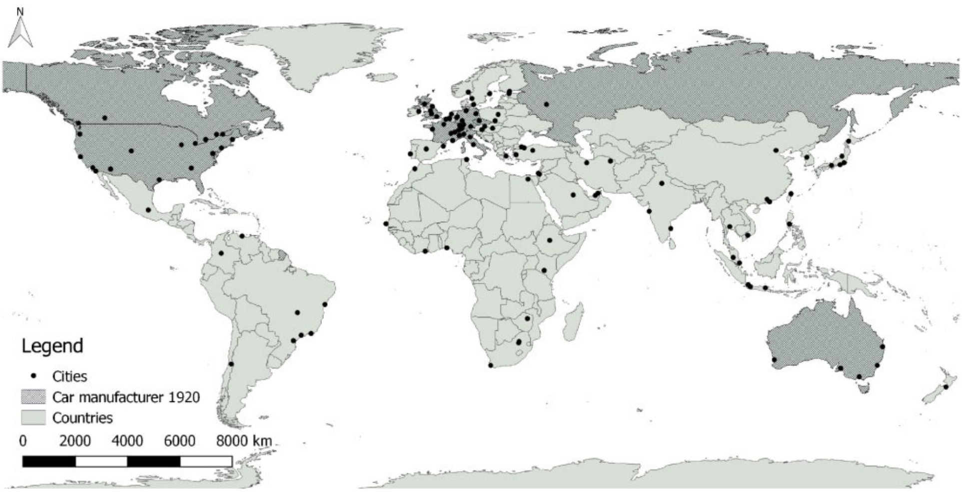

Figure 1. Cities in our dataset.

bulk of home-work journeys in a city. The datasets are then combined, resulting in a total of 232 city observations from 123 cities in 57 countries spanning between 1960 and 2012 (see Table A1 in Online Appendix A which presents the full list of countries and city-year observations).

Population density is our main measure of urban structure, but we also examine other measures such as employment density and centrality of employment. The latter are, however, only observable for MCD1995 and MCD2012. Population density is measured as the total population in a metropolitan area divided by the total built-up area (in km^2).[2] Therefore, it captures the density of developed land, accounting for geographical factors such as water and green space, which may limit density.

These data sources additionally include information on car ownership per capita, metropolitan GDP per capita and highway length, and the MCD1995 dataset also contains car-related variables such as the average cost of a car trip, annual capital costs of a car and the number of kilometres of roads and highways. We also collect climate and elevation data from Fick and Hijmans (2017) and Reuter et al. (2007) using longitude and latitude coordinates of each city centroid. This allows us to compute average January and July temperatures, annual precipitation, altitude and the terrain's ruggedness. We use a similar measure as Burchfield et al. (2006) and calculate ruggedness as the standard deviation of altitude within 50 km from a city's centroid.

To construct our instrument, we collect information on whether a country had a domestic car manufacturer in 1920 by cross-referencing a historical record of all car models and manufacturers in the early 20th century, documented in Doyle's (1957) book *The Worlds Automobiles 1880–1955*.[3] We focus on 1920 because car ownership rates were still very

2 The built-up area includes gardens and local parks, urban wasteland, transport infrastructure, recreational, residential, industrial, office, commercial, public utilities, hospitals, schools, cultural areas and sports grounds.

3 In an earlier version of this paper, we cross-reference the *Timeline of Motor Vehicle Brands* (Wikipedia, 2018); however, this led to the omission of Belgium as an early car manufacturing country. We thank an anonymous referee for the suggestion of using this more comprehensive source.

low, and domestic car manufacturers did not yet have serious political influence at the national level, which is important for the instrument validity. For the instrument to be relevant, we focus on domestic car manufacturers that are likely to have had substantial political leverage at the national level over the majority of the 20th century. Hence, we exclude subsidiaries and niche or boutique car companies. More specifically, we exclude car companies that are partly or entirely owned by a foreign holding company and those that only produce luxury models. For example, we exclude a subsidiary of the Ford Motor Company founded in 1919 (Brazil), a subsidiary of the German auto manufacturer Daimler-Motoren-Gesellschaft, named 'Austro-Daimler' founded in 1899 (Austria) and a luxury car manufacturer called 'Hispano-Suiza' founded in 1904 (Spain). In Online Appendix A.3, we document which domestic car manufacturers were present in each specific country, the year they opened and (if relevant) the year they closed down, including primary sources.

To complement our historical instrument, we also collect historical country-level data on population and GDP per capita for 1913, just before WWI began, from Bolt et al. (2018).[4] Finally, we construct a measure for population density for a representative city in 1920 using data from Goldewijk et al. (2017), as this information is not available using existing sources. We describe the procedure to calculate 1920 population density in Online Appendix A.2.

2.2. Descriptive statistics

Descriptive statistics are provided in Table 1. Population density is around 7,300 people per km^2 and the number of cars per capita is 0.32, on average. An average city in our sample is large, containing a population of around 4.2 million and spanning a built-up area of around 870 km^2, about 36% of the total city surface area. About 45% of cities are located in counties with a car manufacturer in 1920. We provide additional histograms of the main variables of interest in Figure A2 of Online Appendix A.4. They show, for example, that most cities have population densities below 10,000 people per km^2, with a median of around 5,600.

The cities we focus on are rather large and represent labour market areas. Hence, employment density is highly correlated to population density (the correlation is 0.92). In the analysis, we focus on the effect of car ownership on population density and we repeat the main specifications with employment density and other measures in Section 4.3. Figure 2, left plot, shows that the bivariate relation between car ownership per capita and population density of cities is approximately log-linear and strongly negative. The right plot of Figure 2 confirms that message when aggregating our data at the country level.[5] It also shows that countries with historic car manufacturers have notably higher rates of car ownership and lower population densities. In line with common knowledge, US and Australian cities tend to have the highest rates of car ownership and lowest urban densities.

4 Most domestic car manufacturers were present before 1920. Therefore, it seems appropriate to use information for other historic variables slightly prior to 1920.

5 We calculate the urban density in a country by considering population in and area size of urban areas in our sample.

Table 1. Descriptive statistics

	N	Mean	Std. dev	Min	Max
Population density (pop/km^2)	232	7342.44	6473.72	530.00	35,564.53
Employment density (jobs/km^2)	144	3169.18	2712.12	280.00	15,127.67
Cars per capita	232	0.32	0.20	0.00	0.84
Car km per capita (100 km)	123	41.90	37.45	0.36	201.97
GDP per capita ($1000)	232	22.24	21.18	0.22	104.63
Population (millions)	232	4.23	4.92	0.24	37.24
Total built-up area (km^2)	232	874.98	1217.04	44.29	10,657.15
Total surface area (km^2)	153	4293.09	8043.50	126.09	57,378.00
Built-up to surface area	153	0.36	0.23	0.03	0.93
January temperature (°C)	232	9.31	10.26	−10.40	27.60
July temperature (°C)	232	21.47	5.68	8.80	35.30
Annual precipitation (m)	232	0.97	0.56	0.03	2.93
Altitude (km)	232	0.39	0.53	−0.00	2.60
Ruggedness	232	0.18	0.22	0.00	1.68
Car manufacturer 1920	232	0.45	0.50	0.00	1.00
Country Pop 1913 (millions)	232	49.63	88.85	0.08	437.14
Country GDP per capita 1913 ($1000)	232	3.77	2.67	0.38	8.38
Pop dens. 1920 (pop/km^2)	232	8689.51	9900.78	1308.93	77,736.80
Source: Ingram and Liu, 1960	232	0.06	0.24	0.00	1.00
Source: Ingram and Liu, 1990	232	0.11	0.32	0.00	1.00
Source: MCD, 1995	232	0.53	0.50	0.00	1.00
Source: MCD, 2012	232	0.29	0.46	0.00	1.00

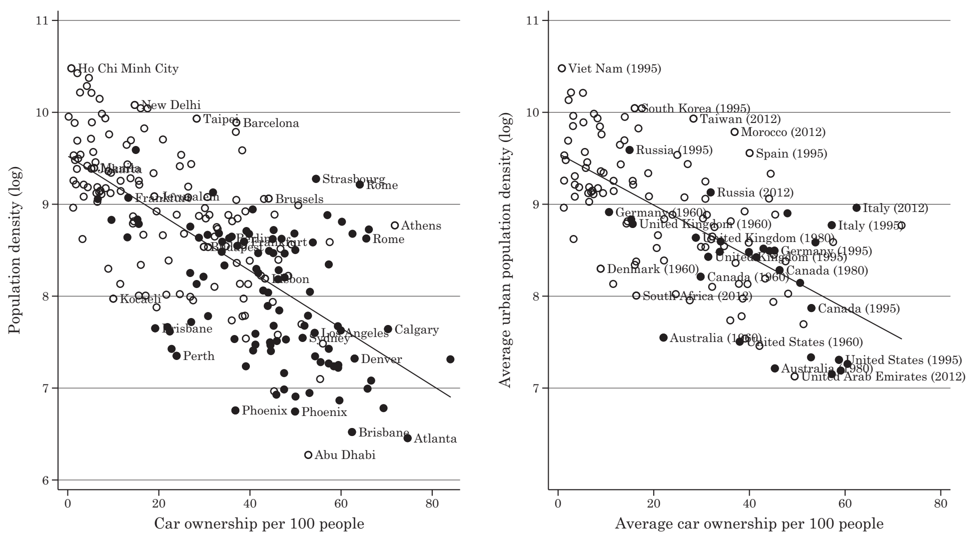

Figure 2. Population density and car ownership per capita.

Notes: The left plot shows city-year data and the right plot shows country-year data. Filled (black) circles represent cities or countries with a domestic car manufacturer in 1920. City and country labels are based on minimum, median and maximum population densities for each bin of 10 cars per 100 people. The solid line represents the bivariate linear regression.

3. Empirical framework

We aim to estimate the long-run causal effect of car ownership per capita on population density. Indexing city i in country j at time t, we set up the following regression equation:

$$\log(D_{ijt}) = \alpha + \beta C_{ijt} + \gamma X_{ijt} + \zeta G_j + \phi_t + \epsilon_{ijt}, \tag{1}$$

where $\log(D_{ijt})$ is the natural logarithm of population density, C_{ijt} represents car ownership per capita, X_{ijt} and G_j are vectors of observed city and country characteristics, ϕ_t are decade fixed effects and ϵ_{ijt} is an error term. Note that for some cities, we have more than one observation. We address this by using weights, with weights inversely proportional to the number of observations per city. As observations do not come from exactly the same year, we control for decade-fixed effects, ϕ_t, in all specifications.

Estimating the marginal effect β with OLS gives consistent estimates of the causal effect of car ownership on urban density, provided that $\mathrm{cov}(C, \epsilon | X, G) = 0$. There are at least two endogeneity concerns when estimating Equation (1) by OLS. First, we may omit important variables which affect both population density and car ownership. Second, changes in the urban structure may lead to changes in mobility, resulting in reverse causation as cities with lower densities may induce more car ownership, which may cause lower densities (Duranton and Turner, 2018).

To tackle the first issue, we include a range of important controls. Higher incomes are correlated with higher rates of car ownership and lower population densities as people demand more housing space per person (Margo, 1992; Dargay, 2002). Therefore, we control for the log of GDP per capita at the city level.[6] Geographical factors such as the climate, altitude and ruggedness of terrain might also affect car ownership and urban density. Gardens are more attractive in warmer climates, construction is more expensive in hilly terrain and active modes of transport like cycling are less likely (Burchfield et al., 2006). Therefore, we control for January and July temperatures, precipitation, altitude and ruggedness. The regulatory environment and cultural factors may also play a role in determining attitudes towards car ownership and urban planning (Duranton and Puga, 2015). La Porta et al. (1999, 2008) argue that legal origins influence a broad range of rules and regulations and find that civil law countries tend to be more regulated than common law countries. We therefore control for English, French, German and Scandinavian legal origins to capture the potential correlation between land-use and vehicle regulations which may affect both population density and car ownership.

To examine omitted variable bias of OLS estimates, we also perform a bias-correction approach which allows us to place a bound on the OLS estimate of β, denoted β_{OLS}, in the presence of omitted variables. Oster (2019) shows that a consistent estimate of the bias-adjusted treatment effect can be calculated given assumptions on two key parameters: (i) the proportion of car ownership explained by unobservables relative to observables, δ, and (ii) the maximum variation in the log of population density that can be explained by

6 Note, whether richer households chose to live closer or further from the city centre depends on the sign of the housing and commuting elasticity with respect to income. In European cities, where the urban core is characterised by strong residential and workplace amenities, richer households are likely to locate closer to the centre (Brueckner et al., 1999; Gutiérrez-i Puigarnau et al., 2016; Gaigné et al., 2020).

observables and unobservables, R^2_{max}.[7] To further address concerns related to omitted variable bias, we also estimate fixed-effects models in Section 4.5.1.

In order to tackle the issue of reverse causality, we require a long-term exogenous shock in the use of automobiles. Glaeser and Kahn (2004) apply an IV approach, using legal origin (French civil law) as an instrument for car ownership, so identification is based on country differences. Legal origin may be argued to be a plausible instrument as it predates the invention of the car, and countries with French civil law tend to be more regulated, hence face higher vehicle costs. However, as mentioned above, one criticism is that because countries with French legal origins tended to have more regulation, the instrument may also impact urban density directly via other stricter regulations such as urban planning (La Porta et al., 2008).[8] Another issue is that in our dataset, the instrument appears to be weak (the F-statistic is 2.78).

We therefore propose the presence of a domestic car manufacturer in a country in 1920 as an alternative instrument for car ownership per capita.[9] In the 1920s, few people owned cars. At that time, the US led the world in car manufacturing and ownership. Nevertheless, there were only 8 million registered cars in the US and the ownership rate was only 0.08.[10] Except for in the US, car ownership and the construction of highways only started to rise in the world after the 1950s. As car ownership began to rise, so did the political leverage of large domestic car manufacturers. Due to their size and scope, throughout the middle to late 20th century, domestic car manufacturers had a powerful lobby, particularly in their home market, to limit vehicle taxes, neglect public transport and advocate for more road construction and parking in cities (Reich, 1989; Paterson, 2000; Dicken, 2011). One may wonder why we do not use, say, 1950 instead of 1920 as the reference year. When including domestic car manufacturers from more recent years, the first stage is likely stronger, but at the same time, it is more likely that the instrument is related to omitted variables that are correlated with car ownership and population density. Hence, we prefer to use car manufacturers from earlier times (we provide robustness of the results of the choice of reference year in Online Appendix B.6).

We emphasise here that we are not the first study to argue for the impact of the automotive industry on current car policy. Probably, the most well-known example of how the automotive industry affected car policies is the so-called Streetcar Conspiracy, where General Motors and other car manufactures were convicted of monopolising the sale of buses and accused of controlling the transit system in order to dismantle existing streetcar networks, which were replaced by buses (Richmond, 1995). In Europe, Cleff et al. (2005)

7 Oster (2019) recommends to use $R^2_{max} = 1$ as an upper bound, which implies that any bias will be overstated. Our estimator sometimes delivers multiple solutions if the importance of unobservables is low, that is $\delta \leq 1$. We then select the solution closest to β_{OLS}, as the alternative solution provides outlier estimates that are not in line with any other specification. In case that the importance is high, that is $\delta > 1$, which is the more interesting case, we only obtain single solutions.

8 For example, Titman and Twite (2013) find that a countries' legal origin is correlated to the building's lease duration and to the number of high-rise office buildings, and therefore may affect urban density directly.

9 The presence of a car manufacturer at the city level is less likely to be exogenous for two reasons. First, manufacturing plants were large and employed many workers. Therefore, car manufacturers may have had a direct effect on the urban structure at the local level. Second, in most countries, national governments determine levels of vehicle and fuel taxation, as well as the layout of highways, which are the mechanisms through which car ownership is likely higher.

10 The US had 8,132,000 registered automobiles and a population of 106,461,000 in 1920 (US Census, 2000). Car ownership was much lower in 1910 and is estimated to be around 500,000. In Section 4.5, we exclude the US as a sensitivity check.

find that EU 'member states having a large car industry tend not to apply a registration tax, or they apply a lower registration tax, while car importing member states tend to levy a higher registration tax'. There is also anecdotal evidence that the automotive industry in France launched a powerful lobby in the 1950s against railways in order to promote road construction (Meunier, 2002).

Many large domestic car manufacturers during the 1900s began in the early 20th century, but not all. Countries such as Japan, South Korea, Spain, and Sweden also developed a substantial capacity to manufacture cars, while car manufacturers also set up plants and subsidiaries in other countries. In both cases, however, the political influence was likely smaller than in the early car manufacturing countries because these industries were active for a shorter period and there is a tendency to support domestic industries as opposed to foreign subsidiaries. Nevertheless, if these countries are also treated with lower vehicle costs, our IV estimate remains unbiased, but our first-stage F-statistic will be weaker.

Countries with a historic car manufacturer after 1920 are therefore likely to have higher rates of car ownership, while the presence of a domestic car manufacturer in 1920 is unlikely to be directly related to urban structure after 1950, other than via car ownership. We will also demonstrate that car manufacturers were not more likely to start up in countries with lower 1920 population density.[11] Furthermore, one may argue that our instrument is *conditionally valid* on the level of economic development in 1920, as more industrialised countries were more likely to have a domestic car manufacturer. GDP in 1920 may be correlated to current car ownership and urbanisation rates. We therefore also estimate specifications where we condition on GDP per capita and population at the country level in 1913. We present further evidence, including several mechanisms and the plausibility of the instrument in Section 4.2.

4. Results

We first present OLS results of the relation between car ownership and population density (Section 4.1), then present evidence on the plausibility of our instrument (Section 4.2), and the IV results (Section 4.3). Finally, we discuss some extensions (Section 4.4) and perform a range of robustness checks (Section 4.5).

4.1. OLS results

In the column (1) of Table 2, we regress the log of population density on cars per capita, controlling only for decade-fixed effects. There is a strong and statistically significant negative association. One additional car per 100 inhabitants is associated with a reduction in average population density of $100 \cdot (\exp(0.0307) - 1) = 3.1\%$. In column (2), we control for GDP per capita, but the effect of car ownership hardly changes.[12]

In Table 6 (OLS results) columns (3)–(5), we include historical population density in 1920 and some additional geographical and legal origin controls. The coefficient of

11 Hence, we address the issue that residents of cities that were more dense before the introduction of the car may have adopted fewer cars and therefore remained more dense.

12 Note that GDP per capita, or income, does not have a statistically significant effect on population density when controlling for car ownership. This result holds regardless of functional form (results from including GDP per capita linearly or with quadratic terms are available upon request). As we will see that income has a strong positive effect on car ownership, in line with Dargay (2002), the overall effect of income on population density appears to be via increased car ownership (see first-stage results in Table 3).

historic population density is positive and statistically significant with an elasticity of 0.46, indicating that density is persistent over time. Including 1920 population density reduces the coefficient of interest slightly to –2.4%, meanwhile there is no noticeable effect from the inclusion of climate and terrain controls in column (4).[13] The coefficient on car ownership declines somewhat in column (5) when controls for legal origin are included. The results indicate that countries with French and German legal origins have higher urban densities than countries with English and Scandinavian legal origins. The effect of one additional car per 100 inhabitants is associated with a reduction in population density of around 2.2% and is statistically significant at the 1% level.

Let's now consider Oster's (2019) bias-adjusted estimate. Under the recommended assumption of $\delta = 1$ and $R^2_{\max} = 1$, the bias corrected estimate is –0.043, with a 95% confidence interval between $[-0.060, -0.025]$.[14] We also loosen the assumptions on the δ parameter (see Figure B1 in Online Appendix B.1). For $\delta \in [0.75, 2]$, we calculate the bounds as $[-0.045, -0.038]$ with an average estimated effect of –0.039. As δ increases, the causal estimate converges to around –0.037. This suggests that the OLS coefficient may be somewhat downwards biased. We will see that bias-corrected estimates are also somewhat larger than the IV results in Section 4.3.

4.2. Domestic car manufacturers in 1920

There is a priori no reason why city structure in 1920 was related to the presence of a domestic car manufacturer in 1920 because few people owned cars. Meanwhile, over the subsequent decades, domestic car manufacturers gained substantial political leverage and had a strong lobby in their home market to increase car demand (Reich, 1989; Paterson, 2000; Dicken, 2011).

To investigate the latter, we will now examine how the presence of a historic domestic car manufacturer is associated with lower generalised prices for car use at the end of the 20th century.[15] In 1920, 10 countries had a domestic car manufacturer.[16] In Table 2, we provide empirical evidence that these countries had lower ownership taxes and lower costs of car use in 1995, even when we control for GDP per capita and other controls. Note that we have slightly fewer observations here than in the main analysis because of missing information. Column (1) indicates that the monetary price of an average car trip, which includes both variable and fixed costs, in 1995 is about 30% lower in countries with historic car manufacturers.[17] Furthermore, these countries have lower annual capital car costs (which include taxes, column (2)), more roads (column (3)) and more highway kilometres per capita (column (4)). However, as these effects are imprecisely estimated, they should

13 Climate, as proxied by January and July temperatures, may be correlated to both driving and building types. Both the OLS results and the first-stage results (see Table 3) do not indicate this to be the case.

14 Standard errors are cluster-bootstrapped (250 replications) and based on countries.

15 The MCD1995 dataset includes information on transport-related costs; however, we also have information on road and highway length for a larger sample of cities and time periods.

16 Australia, Belgium, Canada, the Czech Republic, France, Germany, Italy, Russia, the UK and the US. See Online Appendix A.3.

17 One may be worried that first-stage standard errors are underestimated because of spatial autocorrelation in the errors due to persistence in unobservables characteristics of locations (Kelly, 2019). We do not worry too much about this issue because our instrument is at the country level. Note that our unit of analysis is cities and we include clustered standard errors at the country level so that we fully address the issue of correlated unobservables within countries. Moreover, we are mostly interested in the second-stage results and we provide several robustness checks that suggest that our results are robust.

Table 2. Underlying mechanism

	(1) Car trip cost	(2) Capital cost	(3) Road length	(4) Highway length
Car manufacturer 1920	−0.316*	−0.123	0.323	0.0830
	(0.174)	(0.154)	(0.224)	(0.237)
Controls	Y	Y	Y	Y
Decade FE	Y	Y	Y	Y
R^2	0.615	0.686	0.675	0.576
Number of countries	43	43	50	44
Number of cities	89	92	108	94
Number of observations	89	92	200	124

Notes: Estimates are weighted by the number of observations per city. Dependent variables are in logs. See Table 13 in Online Appendix for descriptive statistics. Car trip cost is defined as the direct user cost of an average car trip and includes depreciation, fuel, spare parts, insurance and taxes. Capital cost is defined as the annual fixed costs which include depreciation, insurance and taxes. Controls are the log of GDP per capita, 1920 population density, January and July temperature, annual precipitation, altitude, ruggedness and legal origin fixed effects, as in column (5) of Table 6. Road and highway length are per capita. Robust standard errors are in parenthesis and are clustered at the country level. Statistical significance is denoted as: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

be interpreted with caution. In Online Appendix A.3, we also document that in 2005, countries with a historical car manufacturer in Europe charge between 20–40% lower vehicle taxes overall, and face almost zero registration taxes, while fuel taxes are somewhat higher (Kunert and Kuhfeld, 2007).

We present the first-stage results of the IV estimates in Table 3. Columns (1)–(5) indicate that the presence of a domestic car manufacturer in 1920 is a strong instrument.[18] The Kleibergen–Paap first-stage F-statistic is 18.8 in the last (and preferred) specification. The instrument has the expected positive sign: countries with a car manufacturer owned around 15 more cars per capita (or around 50% more than the mean city in our sample).[17]

We come now back to our claim that a priori, there is no reason why population density in 1920 was related to the presence of a domestic car manufacturer in 1920. In Table 4, we examine whether countries with a car manufacturer in 1920 were more likely to have cities with lower population densities, as arguably, the instrument is more convincing if it is not related to population density in 1920. Columns (1) and (2) indicate that the presence of a historic domestic car manufacturer is not correlated to historic population density, independent of whether we include controls. If anything, the point estimate in the preferred specification in column (2) suggests that population density was higher in countries with a car manufacturer in 1920.[19]

We also estimate the reduced-form effect on current population density (after 1960) in columns (3) and (4). The results indicate that the presence of a domestic car manufacturer in 1920 has a strong, negative, and statistically significant, effect on population density

18 Note that car ownership at the city level strongly increases with GDP per capita and falls with historic population density.

19 This is not surprising given that, for example, US cities faced higher urban densities until 1950, after which they began to decline (Kim, 2007).

Table 3. First-stage results

	Cars per 100				
	(1)	(2)	(3)	(4)	(5)
Car manufacturer 1920	28.13***	15.79***	15.96***	15.98***	15.13***
	(4.578)	(3.669)	(3.136)	(2.823)	(3.494)
GDP per capita (log)		9.251***	8.331***	8.252***	8.236***
		(0.756)	(0.732)	(1.049)	(1.065)
Pop dens. 1920 (log)			–4.324**	–4.821**	–4.411**
			(1.899)	(1.874)	(1.871)
Climate controls	N	N	N	Y	Y
Terrain controls	N	N	N	Y	Y
Legal origin FE	N	N	N	N	Y
Decade FE	Y	Y	Y	Y	Y
R^2	0.499	0.726	0.748	0.763	0.766
First-stage F-statistic	37.76	18.51	25.92	32.06	18.76
Number of countries	57	57	57	57	57
Number of cities	123	123	123	123	123
Number of observations	232	232	232	232	232

Notes: Estimates are weighted by the number of observations per city. Robust standard errors are in parenthesis and are clustered at the country level. See Table B1 in Online Appendix B.6 for table including all controls. Climate controls are January and July temperatures and annual precipitation, and terrain controls are altitude and ruggedness as in column (5) of Table 2. Statistical significance is denoted as $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Kleibergen–Paap F-statistic is presented.

many years later.[20] Hence, historic car manufacturers are not related to historic population density, but have a causal effect on current density. In the following 2SLS analysis, we control for historic population density, but we emphasise that the results of Table 4 imply that our instrument is also unconditionally valid, that is, when not controlling for historic population density, we will obtain the same effect for car ownership.

4.3. IV results

In Table 5, we provide the 2SLS results using the presence of a historic domestic car manufacturer as an instrument. The coefficient of interest remains quite stable to the inclusion of control variables and is of a similar order of magnitude to the OLS estimates. Furthermore, the control variables have a similar effect when compared with the OLS estimates in Table 6.

The preferred specification in column (5) indicates that one additional car per 100 inhabitants is associated with a reduction in population density of around 2.2%. This is essentially identical to the OLS results and a Hausman test does not reject the null hypothesis that the IV and OLS coefficients on cars per 100 in column (5) are significantly different from each other.[21] Apparently, the reverse causality issue is too small to have

20 A formal test for the difference between the effect of car manufacturers in Equations (2) and (4) rejects the null hypothesis that there is no difference at the 95% confidence level. The difference is –0.62, with a standard error of 0.26 and a corresponding t-statistic of –2.40.

21 We perform a cluster-robust Hausman test with 250 bootstrap replications (Cameron and Trivedi, 2005). The test statistic is $\chi^2(1) = 0.00$, with a corresponding p-value of 0.99.

Table 4. Additional validity tests of instrument

	Population density 1920 (log)		Population density (log)	
	(1)	(2)	(3)	(4)
Car manufacturer 1920	−0.243	0.224	−0.797***	−0.329**
	(0.265)	(0.214)	(0.287)	(0.162)
Decade FE	Y	Y	Y	Y
Controls	N	Y	N	Y
R^2	0.0548	0.279	0.223	0.657
Number of countries	57	57	57	57
Number of cities	123	123	123	123
Number of observations	232	232	232	232

Notes: Estimates are weighted by the number of observations per city. The dependent variable is historic (1920) or observed (1960–2012) population density in logs. Robust standard errors are in parenthesis and are clustered at the country level. Controls are the log of GDP per capita, January and July temperature, annual precipitation, altitude, ruggedness, legal origin-fixed effects and in columns (3) and (4) we also include 1920 population density, as in column (5) of Table 6. Statistical significance is denoted as $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 5. 2SLS estimates

	Population density (log)				
	(1)	(2)	(3)	(4)	(5)
Cars per 100	−0.0283***	−0.0243*	−0.0255***	−0.0230**	−0.0217**
	(0.00714)	(0.0133)	(0.00983)	(0.00998)	(0.0100)
GDP per capita (log)		−0.0841	0.0225	−0.0436	−0.0351
		(0.146)	(0.108)	(0.108)	(0.113)
Pop dens. 1920 (log)			0.450***	0.429***	0.357***
			(0.0749)	(0.0753)	(0.0681)
Climate controls	N	N	N	Y	Y
Terrain controls	N	N	N	Y	Y
Legal origin FE	N	N	N	N	Y
Decade FE	Y	Y	Y	Y	Y
First-stage F-statistic	37.76	18.51	25.92	32.06	18.76
Number of countries	57	57	57	57	57
Number of cities	123	123	123	123	123
Number of observations	232	232	232	232	232

Notes: Estimates are weighted by the number of observations per city. See Table B2 in Online Appendix B.6 for table including all controls. Climate controls are January and July temperatures and annual precipitation, and terrain controls are altitude and ruggedness as in column (5) of Table 6. Robust standard errors are in parenthesis and are clustered at the country level. Kleibergen–Paap F-statistic is presented. Statistical significance is denoted as $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 6. OLS estimates

	Population density (log)				
	(1)	(2)	(3)	(4)	(5)
Cars per 100	-0.0307^{***}	-0.0302^{***}	-0.0243^{***}	-0.0236^{***}	-0.0218^{***}
	(0.00490)	(0.00705)	(0.00541)	(0.00554)	(0.00620)
GDP per capita (log)		−0.0115	0.00803	−0.0373	−0.0346
		(0.0773)	(0.0564)	(0.0593)	(0.0695)
Pop dens. 1920 (log)			0.455^{***}	0.426^{***}	0.356^{***}
			(0.0706)	(0.0705)	(0.0621)
January temperature (°C)				−0.00917	−0.00821
				(0.00665)	(0.00696)
July temperature (°C)				0.0118	0.00869
				(0.0125)	(0.00981)
Annual precipitation (m)				0.182	0.173
				(0.136)	(0.122)
Altitude (km)				-0.182^{*}	-0.185^{**}
				(0.103)	(0.0792)
Ruggedness				0.541^{**}	0.292
				(0.247)	(0.198)
French legal origin					0.476^{***}
					(0.148)
German legal origin					0.302^{**}
					(0.151)
Scandinavian legal origin					−0.274
					(0.170)
Decade FE	Y	Y	Y	Y	Y
R^2	0.502	0.502	0.623	0.660	0.715
Number of countries	57	57	57	57	57
Number of cities	123	123	123	123	123
Number of observations	232	232	232	232	232

Notes: Estimates are weighted by the number of observations per city. Robust standard errors are in parenthesis and are clustered at the country level. Statistical significance is denoted as: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

consequences for the estimates, at least at the city level.[22] The estimate implies that a one standard deviation increase in car ownership (20 cars per 100 inhabitants) is associated with a change in population density of $\exp(\hat{\beta} \times \Delta C) - 1 = \exp(-0.022 \times 20) - 1 = -36\%$. We find a smaller effect than in Glaeser and Kahn (2004) who find an effect size around three times as large (see their Table 5, column (3), which is 7.2%).

4.4. Extensions

4.4.1. Other dependent variables

In Table 7, we present results separating population density into population and area size of the city, and consider two additional dependent variables: employment density and

22 Duranton and Turner (2018) find that urban density has a small negative effect on vehicle kilometres driven; however, their study is at the household level rather than the city level.

Table 7. 2SLS sensitivity checks: Other dependent variables

	(1) Population	(2) Area	(3) Emp. density	(4) Prop. Jobs CBD
Cars per 100	−0.00309	0.0186	−0.0157	−0.00818
	(0.0155)	(0.0204)	(0.0106)	(0.0126)
Controls	Y	Y	Y	Y
Decade FE	Y	Y	Y	Y
First-stage F-statistic	18.76	18.76	14.50	17.64
Number of countries	57	57	53	46
Number of cities	123	123	112	112
Number of observations	232	232	144	93

Notes: Dependent variables are in logs. Estimates are weighted by the number of observations per city. Controls are the log of GDP per capita, 1920 population density, January and July temperature, annual precipitation, altitude, ruggedness and legal origin fixed effects, as in column (5) of Table 6. Robust standard errors are in parenthesis and are clustered at the country level. Kleibergen–Paap F-statistic is presented. Statistical significance is denoted as $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

employment centrality, defined by the number of jobs in the CBD. columns (1) and (2) indicate that although the effect of car ownership rates is not statistically significant when regressing both variables separately, the point estimate of cars per 100 on the log of built-up area is 0.019, which is essentially identical to the estimate of cars on population density in column (5) of Table 5, meanwhile, the point estimate on population is essentially zero. This is in line with the sprawl hypothesis as it suggests that the overall effect of cars on population density appears to be via cars causing cities to spread out further (Glaeser and Kahn, 2004; Nechyba and Walsh, 2004; Su and DeSalvo, 2008).

As mentioned in Section 2, population and employment density are highly correlated; therefore, one expects similar effects for population and employment density. Baum-Snow (2010) also finds similar effects of highways on the decentralisation of firms and households. column (3) indicates that one additional car per 100 inhabitants is associated with a slightly smaller reduction in employment density of around 1.6%, but this effect is not statistically significant. We also examine whether car ownership rates reduce the proportion of jobs in the CBD in column (4), however, we only find an imprecise negative effect.

4.4.2. Heterogeneous effects

We also investigate whether the effect of car ownership on population density varies by (i) infrastructure quality (length of roads and highways), (ii) level of GDP, and (iii) origin of law system. Importantly, when we focus on the interaction with infrastructure quality, we will also control for the main effect of infrastructure quality (for a more in-depth discussion and analysis of including infrastructure quality as an additional control, see Online Appendix B.4). Table 8 reports the results.[23] Columns (1) and (2) suggest that roads and

23 To improve efficiency of the estimates, we include interactions of the fitted values from the first-stage with road length, GDP per capita and legal origin. We refer to Levkovich et al. (2019) who compare different methodologies to deal with interactions when applying IV.

Table 8. 2SLS sensitivity checks: Heterogeneity

	Population density (log)			
	(1) Road length	(2) Highway length	(3) GDP	(4) Legal origin
Cars per 100 (demeaned)	−0.0147*	−0.0128	−0.0140	−0.0305***
	(0.00860)	(0.0106)	(0.0114)	(0.00923)
× Road length demeaned (log)	−0.00814***			
	(0.00178)			
× Highway length demeaned (log)		−0.00793***		
		(0.00227)		
× GDP per capita demeaned (log)			−0.00468**	
			(0.00215)	
× French origin				0.0234***
				(0.00451)
× German origin				0.00238
				(0.00651)
× Scandinavian origin				−0.0111
				(0.0130)
GDP per capita demeaned (log)			−0.182	
			(0.151)	
Road length demeaned (log)	−0.115***			
	(0.0400)			
Highway length demeaned (log)		−0.0471		
		(0.0549)		
GDP per capita (log)	−0.152	−0.197		−0.0400
	(0.119)	(0.151)		(0.108)
French legal origin	0.341**	0.472***	0.497***	0.509***
	(0.156)	(0.174)	(0.152)	(0.133)
German legal origin	0.146	0.251	0.352*	0.258
	(0.204)	(0.212)	(0.199)	(0.183)
Scandinavian legal origin	−0.210	−0.263	−0.112	−0.210
	(0.228)	(0.309)	(0.270)	(0.221)
Controls	Y	Y	Y	Y
Decade FE	Y	Y	Y	Y
First-stage *F*-statistic	18.76	18.76	18.76	18.76
Number of countries	50	44	57	57
Number of cities	200	124	232	232

Notes: Estimates are weighted by the number of observations per city. Controls are 1920 population density, January and July temperature, annual precipitation, altitude, ruggedness and legal origin fixed effects, as in column (5) of Table 6. Robust standard errors are in parenthesis and are clustered at the country level. Kleibergen–Paap F-statistic is presented. Statistical significance is denoted as $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

highways appear to have a complementary effect, so both roads *and* cars are important in facilitating urban decentralisation. It appears that roads have a statistically significant and negative direct effect on population density, while the direct effect of highways is a lot smaller. However, we should not draw too strong conclusions because roads and highways are likely to be endogenous, as acknowledged by Baum-Snow (2007).

In column (3), we find some evidence that the effect of car ownership on population density is larger in countries with a higher GDP. This result might be reasonable as richer countries are likely to invest in road infrastructure that strengthens the effect of car ownership.

Finally, column (4) indicates that while the effect of car ownership appears to be similar for countries with English, German and Scandinavian legal origins, countries with French legal origins appear to have significantly smaller effects (around half). This indicates that countries with French legal origins are not only more regulated in terms of taxation (Glaeser and Kahn, 2004) but also have more planning restrictions.

4.5. Robustness

The OLS and IV results indicate that one additional car per 100 inhabitants reduces population density at the city level by 2.2% in the long-run. This subsection performs a wide range of robustness checks and provides some tentative evidence on the middle-run effect.

4.5.1. Fixed-effects models

Up to now, we have exploited (mainly) cross-sectional variation in population density and car ownership. We assess the sensitivity of our results to various alternative types of variation by gradually including a more detailed set of fixed effects. The first column of Table 9 shows IV results and columns (2)–(5) show OLS results. In columns (1) and (2), we include continent fixed effects. The limitation of this analysis is that because our instrument varies at the country level, the degrees of freedom at the country level are strongly reduced. As a consequence, the first-stage F-statistic falls below 10 and the coefficient of interest becomes imprecise. Nevertheless, including continent fixed effects leads to a similar result as our main specification.

Next, we include country-fixed effects. Therefore, we only exploit cross-sectional variation *within* a country. This has the advantage that we can control for unobserved factors at the national level, such as regulations that affect both vehicle ownership and urban density. However, as our instrument does not vary at the city level, we are unable to correct for reverse causality. So far, our results have shown that the OLS and IV results are remarkably similar, and the OLS results are generally more conservative. Therefore, we tentatively perform this analysis to check the robustness of our results, but urge caution when interpreting the coefficients as causal effects. The results in column (3) indicate that the effect is roughly similar. One additional car is associated with a reduction in population density of around –1.5% and is statistically significant at the 10% level.

We then exploit temporal variation by including city-fixed effects in column (4). This provides a tentative estimate of the middle-run effects. The estimate, however, becomes close to zero and is not statistically significant. An issue with this specification is that urban density changes slowly, and information about cities that are observed with few years in between comes from different sources, implying substantial measurement error. The latter is problematic because the downward bias due to measurement error is compounded with panel data. To overcome the inconsistency, Cameron and Trivedi (2005) recommend using longer differences. Therefore, in specification (5), we only select observations for cities observed at least 20 years apart. This leaves us with 29 cities and 77 observations. The coefficient is −1.5% and statistically significant at the 1% level. This is smaller in magnitude than our main IV result, but around the same size as the

Table 9. Additional sensitivity checks: fixed effects models

	Population density (log)				
	(1) IV	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Cars per 100	−0.0207	−0.0198**	−0.0145*	−0.00374	−0.0156***
	(0.0279)	(0.00840)	(0.00811)	(0.00434)	(0.00488)
Controls	Y	Y	Y	Y	Y
Decade FE	Y	Y	Y	Y	Y
Area FE	Continent (6)	Continent (6)	Country	City	City
R^2		0.742	0.888	0.964	0.967
First-stage F-statistic	4.447				
Number of countries	57	57	57	34	15
Number of cities	107	107	107	60	29
Number of observations	232	232	232	169	77

Notes: Estimates are weighted by the number of observations per city. Controls are the log of GDP per capita, 1920 population density, January and July temperature, annual precipitation, altitude, ruggedness and legal origin fixed effects, as in column (5) of Table 6. Robust standard errors are in parenthesis and are clustered at the country level. Kleibergen–Paap F-statistic is presented. Statistical significance is denoted as $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

OLS result when including country-fixed effects, suggesting that the middle-run effect may be about two thirds of the size of the long-run effect.

4.5.2. Other robustness checks

In Online Appendix B.3, we consider alternative proxies for automobile use. We include motorbike use both as a separate variable, and together with car ownership, leading to similar results. We also consider measuring car usage directly by using car kilometres per capita and car kilometres per car. For car kilometre per capita, we find almost identical results. However, for car kilometres per car, the results are imprecise because of a weak first stage. This may be because domestic car manufacturers focus lobbying efforts on car ownership and purchase while having smaller effects of car usage such as fuel taxes, which is corroborated by our analysis on European countries in Online Appendix A.3. Still, despite weak instruments, we find a negative second-stage coefficient of car use on population density of the same order of magnitude as the baseline estimates.

A large literature has investigated the effects of highways on population density and decentralisation. However, roads and highways are only likely to cause cities to decentralise when there is sufficient car use. In Online Appendix B.4, we further investigate whether the effect of car ownership and infrastructure on population density are complementary, while acknowledging the potential endogeneity of roads (Baum-Snow, 2007). We show that roads and highways are associated negatively with population density. The effect of car ownership is only reduced by about 20%, suggesting that we also expect decentralisation to happen when infrastructure is still immature (e.g. in cities in Sub-Saharan Africa).

Our data are composed of three main data sources, obtained from Ingram and Liu (1999), Kenworthy and Laube (2001) and UITP (2015). In Online Appendix B.5, we assess the sensitivity of our results to the various data sources. There are two important observations from this exercise. The first-stage F-statistic becomes weaker for more recent data and the second-stage estimate becomes smaller. This suggests that domestic car manufacturers were more powerful in the 1960s and 1970s in influencing policy, which is in line with anecdotal evidence. The reduction in the magnitude of the second-stage coefficient appears to be driven by the inclusion of other cities and countries. This suggests that the sample of cities in Ingram and Liu (1999) is not completely representative.

We consider various other robustness checks in Online Appendix B.6. We first make sure that the effect of domestic car manufacturers in 1920 on car ownership is not confounded by GDP per capita around that time, as car manufacturers in 1920 tended to be present in higher-income countries. Although the coefficient of interest becomes imprecise, the magnitude of the point estimate increases slightly and is very close to our preferred baseline estimate.

One may be worried that cities in the US drive our results due to their firmly established car culture and the abundance of land for urban expansion. When we exclude the 12 cities in the US from our sample (27 observations) the effect size decreases slightly to –1.6%. Furthermore, country borders changed over the 20th century. This may affect assignment into treatment as these countries were possibly treated at some point in time but would be mislabelled as non-car manufacturing. Therefore, we exclude countries that were formerly part of the Soviet block. This has no meaningful impact on the second-stage results, while the first-stage F-statistic increases.

As an instrument, we use a dummy whether there is a domestic car manufacturer in 1920. Alternatively, we also consider using a dummy whether there is a domestic car manufacturer in 1910 or 1930. This leads to similar results, although the results are statistically stronger once we use the dummy indicating whether there is a domestic car manufacturer in 1930.

4.6. Implications

Overall, our preferred estimate from column (5) in Table 5 implies that an increase in car ownership of one car per 100 inhabitants leads to a reduction in population density of around 2.2%. This section applies this estimate to gauge the potential effects of growing car ownership rates in developing countries and the introduction of autonomous vehicles on urban density.

4.6.1. Growing car ownership in developing countries

In 1995, cities located in developing Asian countries owned substantially fewer cars per capita and faced higher population densities (see Table A5 in Online Appendix). Applying our estimates suggests that if car ownership increases to similar rates as seen in western Europe, urban density will fall by around 50% in the long-run, while if car ownership rates reach levels seen in North America and Oceania, density would even fall by around 60%.

We have applied our estimates for three Chinese cities in our dataset: Beijing, Guangzhou and Shanghai. In 1995, average car ownership in these cities was 2.6 cars per 100 inhabitants which grew to 17.5 by 2010.[24] According to our results, this would result in a reduction in population density of around 30%. The actual reduction was around 60% (it declined from

24 Information for the year 2010 is gathered from ITF (2017) and Demographia (2010).

14,600 to 5600 people per km^2), suggesting that changes in car ownership explain about half the reduction in population density. However, note that as the period between 1995 and 2010 is relatively short, it is plausible that the contribution of car ownership is less.

4.6.2. Automated vehicles

Our estimates are also relevant in the broader context of future transport developments such as fully AVs which are expected to increase access to cars. These results are particularly relevant to cities with relatively high incomes, but low levels of car ownership, such as Copenhagen (Denmark) and Tokyo (Japan). Currently, car use is limited by ownership. However, AVs are expected to reduce the fixed costs of owning a car, thereby increasing vehicle access. In the absence of policy, our results suggest that cities are expected to become more decentralised.

Fagnant and Kockelman (2015) assume that AVs are expected to increase vehicle kilometres travelled (VKT) by 10–20% in the US. We use our estimate for the change in VKT per capita in column (4) of Table B3 in Online Appendix B.3 and consider these changes as lower and upper bounds of the effects of AVs. In scenario (A), effective car ownership for an average city in our dataset increases by 10%, or 420 km per person, leading to a decline in population density of around 6.5%. In scenario (B), we consider a more extreme situation where equivalent car use increases by 20%, which is expected to result in population density declining by around 12.5% in the long-run.

While these estimates provide a rough indication of the potential effects of AVs, there may be reasons to expect that they may be over or under-estimates. On the one hand, because AVs can be shared and therefore do not require car ownership, this may free up vast amounts of parking space in inner cities, which could be used for residential and other purposes. On the other hand, because commuters can engage in other activities in the vehicle, such as sleeping or working, this might lead to longer commutes than currently tolerated (Pudāne et al., 2019).

5. Conclusions

Cars have dominated the urban landscape over the past century. In this paper, we investigate the long-run impact of car ownership on urban form, in particular on population density, in an international sample of cities. Using the presence of a domestic car manufacturer in 1920 as a source of exogenous long-term variation in vehicle costs, our IV estimates indicate that higher car ownership rates, induced via lower ownership costs, substantially reduce densities. A one standard deviation increase in car ownership rates (or 20 cars per 100 inhabitants) causes a reduction in density of around 35% in the long-run. Disentangling this effect between population and city size suggests that the major driver of this reduction in urban density is via the city's outward expansion as the size of urban areas increases. Furthermore, we find that the effects are larger in cities with more roads, highways and income, while they are lower in countries with French legal origins, which may have stricter vehicle taxation and land-use regulations.

Our findings suggest that unpriced market failures in the car market have additional spillovers on urban density. This has implications for the key benefits of living and working in a city, and may justify higher taxes on private vehicle ownership and use in order to increase the benefits associated with higher densities, such as positive agglomeration economies and public transport efficiency, and decrease the costs associated with lower densities, such as pollution and environmental damage. Furthermore, the paper also has implications for expected urban growth in developing countries, where car ownership rates and populations are rapidly increasing, and future transport technologies such as AVs, which are expected to reduce the costs of using a private vehicle dramatically.

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Supplementary material

Supplementary data for this paper are available at *Journal of Economic Geography* online.

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