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Driving over the hill: Car intensity during structural transformation

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Driving over the hill: Car intensity during structural transformation

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This paper examines the number of licensed private cars in the economy per unit of GDP, or car intensity, as an intrinsic component of car use that may be underlying the observed peak car phenomenon. Using data on 88 countries from 1950 to 2010, I demonstrate that car intensity evolves in a hump-shaped pattern during economic development. I develop a general equilibrium model to argue that structural transformation can generate this trend. My calibrated model can account for just under a quarter of observed variation in car intensity among 54 countries in 2010. Counterfactual exercises show that the peak level of intensity is lower for economies that develop later.

Key words: peak car; structural transformation; economic growth; economic development; industrialisation; transport.
JEL codes: O41; N10; O18; R10.

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1. Introduction

Transport accounted for 34 per cent of all carbon dioxide emissions in the United Kingdom (UK) in 2022, with the majority of this stemming from road transport (UK Department for Energy Security and Net Zero 2023a). This is thus a key sector where a reduction in emissions is required to meet the Paris Climate Change Agreement's target of limiting the global temperature rise to 1.5 degrees Celsius (Masson-Delmotte et al. 2018). The United Nations (UN 2021b) has also identified sustainable transport as a key enabler of a range of Sustainable Development Goals. Reductions in motor vehicle use will be required alongside advances in fuel efficiency and in electric vehicle technology to ensure a decrease in carbon emissions.[1] In addition to reduced carbon emissions, a reduction in car use can contribute to congestion relief, improved air quality, increased active travelling, increased wellbeing and improved accessibility (Goodwin 2020).

This study is focused on the level of car use as a country develops, and asks the following questions: How does the dependency of an economy on car use evolve as the economy develops? What role does structural transformation, the redistribution of economic activity among the broad agriculture, manufacturing and services sectors (Herrendorf, Rogerson, and Valentinyi 2014), play in this relationship? In considering these questions, I analyse trends in car use per unit of gross domestic product (GDP), or the level of car use required to produce one unit of GDP, as GDP per capita rises. This can be referred to as the intensity of car use. Uniquely, I will show that among developed economies, the intensity of car use displays an inverted U-shaped or hump-shaped relationship with GDP per capita, increasing initially before peaking and later decreasing. The study will then explore this dynamic by developing a theoretical model of structural transformation capable of reflecting the hump-shape in car use per GDP.

1.1. Peak car

While specifically considering car use per unit of GDP, this study is closely related to the debate in transport literature surrounding 'peak car'. The peak car phenomenon has been described as a levelling off in various measures of car use, such as annual per-capita distance travelled in cars and per-capita car ownership, which has been becoming evident in many developed cities and countries (Webb 2019; Bastian, Börjesson, and Eliasson 2016; Goodwin and Van Dender 2013; Millard-Ball and Schipper 2011). Studies including Puentes and Tomer (2008), Lucas and Jones (2009) and Schipper (2009) began to note a stabilisation of growth in car use per capita, and Millard-Ball and Schipper (2011) coined the phrase

1. While the fuel efficiency of motor vehicles has improved substantially over time, it has been pointed out that such improvements can often be negated by increases in vehicle power, vehicle weight or distance travelled in the form of a rebound effect (Stapleton, Sorrell, and Schwanen 2017). The advent of hybrid and electric vehicles can also contribute to lower carbon emissions, although this is dependent on the decarbonisation of electricity generation (Bahamonde-Birke 2020).

'peak car' to describe this emerging trend.

Millard-Ball and Schipper (2011) collated data from 1970 to 2007 from various sources to show that private vehicle use across 8 industrialised countries had plateaued. A descriptive analysis of household travel survey microdata indicated that car use per capita peaked in Paris, Berlin, London and Vienna in the 1990s, and in Copenhagen in the late 2000s (Wittwer, Gerike, and Hubrich 2019). In most developed countries, car use per capita has been viewed as having stagnated around the 2000s (Bussière, Madre, and Tapia-Villarreal 2019), and Goodwin (2020) noted that there was increasing evidence by around 2010 that per-capita car use was reaching a peak level. King (2020), however, regarded the concept of peak car as an open debate rather than an established phenomenon, suggesting that declining car vehicle kilometres (VKM)[2] in the early 2010s could have been related to economic activity.

Naturally, while peak car is a phenomenon that has become increasingly evident among many developed countries, there has been some interest in whether such patterns could be expected to emerge in countries or cities at an earlier stage of development. Gao and Newman (2018) showed descriptive statistics of car use in the emerging city of Beijing and indicated that car use reduced during the 2010s while GDP continued to increase. Using household survey and population projection data in the developed cities of Lille and Montreal, and in the developing cities of Juarez and Puebla, Bussière, Madre, and Tapia-Villarreal (2019) projected that peak car may be reached in Juarez and Puebla in 2030 based on previous trends in Lille and Montreal.

Numerous factors have been proposed in the literature to explain peak car. One popular factor has been that there must exist a saturation level of car use, either through a saturation of travel demand or via technological constraints. While Millard-Ball and Schipper (2011) did not empirically investigate possible factors, they pointed out that there must be some saturation level for car use given time constraints. Historically, new infrastructure or new technologies have led to increased travel speeds, allowing increased car use for a given time allocation, whereas this increase may have since levelled off (Millard-Ball and Schipper 2011).

Metz (2010) had also made this argument using descriptive evidence from the UK National Travel Survey. The existence of a saturation level of car use was also discussed as a possible factor by Newman and Kenworthy (2011), while Metz (2013) argued that a saturation level of travel demand must exist on the basis that the benefits of travelling longer distances within a given time constraint to widen destination choice would be subject to diminishing marginal returns. Again, however, these hypotheses

2. A common measure of distance travelled by transport mode is vehicle kilometres (VKM), which represents the movement of one vehicle over one kilometre and can be calculated by multiplying the number of vehicles on a road by the average length of their trips. This may be estimated from traffic volume data, or from survey data related to vehicles or their drivers (Jamroz and Wachnicka 2015). An alternative measure is passenger kilometres (PKM), employed as a measure of passenger distance. This is calculated by multiplying the total distance travelled by the number of passengers transported.

were not empirically tested in these studies. An analysis of car travel in France was conducted by Grimal, Collet, and Madre (2013) in which saturation was assumed to be a function increasing in income and decreasing in fuel price and population density.

Given the clear link between VKM and car ownership identified by many studies (for example Jamroz and Wachnicka 2015; Van Acker and Witlox 2010; De Jong et al. 2004), the proposed existence of a saturation level of car use is closely related to a previously hypothesised saturation point in car ownership. Tanner (1978) discussed a theoretical limit of one car per person among the population old enough to drive a car, and pointed to evidence that growth rates in car ownership declined as car ownership increased. That car ownership continued to predict vehicle kilometres travelled by car was also highlighted by Tanner (1978) as an indication that this saturation point existed, as individuals owning multiple cars would imply that average VKM per car would decrease. Tanner (1978) also noted, however, that there was evidence of different levels of saturation in different locations.

Another peak car factor discussed in the literature has been public transport. Newman, Kenworthy, and Glazebrook (2013) presented descriptive statistics using global city level data to argue that rail systems in urban areas have been expanding, increasing in both service levels and utilisation. The study also suggested that the speed of rail in urban areas had been increasing relative to car transport, and that this may be a factor in peak car patterns.

Peak car patterns have also been attributed to a decline in car use among young adults. Delbosc and Currie (2013) reviewed several papers that identified a decrease in young adults holding a driving license. Kuhnimhof et al. (2012) presented National Travel Survey data from 6 industrialised countries that showed a fall in driving license holding and car ownership among young adults, with a more pronounced decline among young men. In an empirical analysis using census data for England, Melia, Chatterjee, and Stokes (2018) found that increasing population density was leading to lower car ownership and more public transport utilisation among young adults. Other factors in these trends among young adults that have been suggested include increasing enrolment in tertiary education and a corresponding lower labour force participation (Delbosc and Currie 2013; Kuhnimhof et al. 2012). However, Kuhnimhof, Zumkeller, and Chlond (2013) noted that while younger cohorts appeared to be contributing most to peak car trends, increased car ownership and driving license holding among older adults was having the opposite effect.

Urbanisation has also been identified as a more general factor in peak car by other studies. An econometric analysis of aggregate time series data since 1970 for Great Britain conducted by Stapleton, Sorrell, and Schwanen (2017) found that the levelling off in car VKM could be explained by increasing levels of urbanisation, in addition to increasing fuel prices and decreases in income following the 2008 financial crisis. Headicar (2013) analysed census and household travel survey data in England from 1970 to show a high level of variation in distances travelled by car between areas depending on their level of urbanisation, and noted that peak car patterns appeared to coincide with a reversal of previous migration trends from urban to suburban locations.

The role of more fundamental economic variables such as income or fuel prices in peak car patterns has not been universally settled in this literature. Goodwin and Van Dender (2013) noted a theme that aggregate models of car travel demand that focused solely on GDP per capita and fuel prices were dismissed as too crude and incapable of explaining more recent trends. Several early studies of peak car including Puentes and Tomer (2008), Metz (2010), Newman and Kenworthy (2011) and Millard-Ball and Schipper (2011) pointed out that the plateau in car use preceded the Great Recession and significant increases in oil prices in 2008, and that other forces must therefore be at play. However, Grimal, Collet, and Madre (2013) found that peak car patterns were evident to some extent across all income groups and levels of urbanisation in France, and argued that this suggested that the main factor must have been a significant and widespread change in economic conditions, such as increases in fuel prices. Using data from 6 developed countries for the period between 1980 and 2013, Bastian, Börjesson, and Eliasson (2016) presented regression modelling that indicated peak car patterns could, in fact, be predicted using only income and fuel price as independent variables, while stressing that this did not preclude other factors from also being influential. The study also found evidence of a declining elasticity of car travel with respect to GDP as GDP per capita increased, which was viewed as consistent with the existence of a saturation level of car use or car ownership. Similar results were also shown specifically for Sweden by Bastian and Börjesson (2015).

Some studies have revealed within-country regional differences in peak car patterns. Metz (2015) showed a stronger decline in car use per capita in London than in the rest of the UK, and suggested that this could have been a reflection of congestion levels or differences in local transport policy. In Sweden, Bastian and Börjesson (2015) highlighted differences in the sensitivity of car use to GDP and fuel prices between the two main cities and the rest of the country, with a higher elasticity evident in cities. The study pointed out that this was consistent with cities offering more public transport and a higher density of possible destinations.

A plethora of other explanations for peak car have been suggested in the literature, including the substitution of car travel by electronic communication (van Wee 2015), lower subsidisation of company cars (Le Vine, Jones, and Polak 2013) and a switch to air travel (Millard-Ball and Schipper 2011). In summary, a consensus in the literature on the factors behind the apparent levelling off in car use per capita among developing countries has remained elusive. As a result of this, the related debates over whether car use has in fact reached a peak level in developed economies and whether it can be expected to decrease into the future have also persisted without agreement.

Considering distance travelled per unit of GDP, as I do in this study, is another lens through which to observe the peak car phenomenon since a persistent idea in the literature has been that car use is strongly related to GDP. The level of car use required in an economy to produce a single unit of GDP could also be thought of as a fundamental factor underlying trends in per-capita car use. Kenworthy (2013) presented a descriptive analysis of city-level data from 1995-1996 and 2005-2006 across the United States (US), Australia, Canada, Europe and Asia that showed reductions in car VKM per unit of GDP, indicating a decoupling of urban car use from GDP, although the study did not empirically test factors behind these trends. Kenworthy (2013) also found that GDP per capita was actually a poor predictor of car VKM per capita among the cities included in the dataset. A high level of cross-sectional variation in VKM per GDP was also apparent, with cities in the US and Australia showing higher levels than cities in Europe, Canada and Asia, despite the general downward trend across all cities (Kenworthy 2013).

1.2. Structural transformation

A separate literature that is relevant to this study has focused on the global phenomenon of structural transformation. This is the reallocation of economic activity among the broad agriculture, manufacturing and services sectors (Herrendorf, Rogerson, and Valentinyi 2014), and has been highlighted as a key feature of modern economic growth (Kuznets 1973). Rogerson (2008) and Herrendorf, Rogerson, and Valentinyi (2014) noted two distinct approaches to modelling structural transformation in multi-sector general equilibrium models that are founded on representative agents. First, in the demand approach, consumer preferences over goods are specified as being non-homothetic (using a form of Stone-Geary preferences), and this gives rise to an 'income effect' with consumers devoting a decreasing share of their budget to agriculture goods as they get richer (for example, Comin, Lashkari, and Mestieri 2021; Boppart 2014; Gollin, Parente, and Rogerson 2002; Kongsamut, Rebelo, and Xie 2001; Echevarria 1997). Second, in the productivity approach, technological growth is considered to be uneven across sectors, leading to a 'substitution effect' or 'price effect' with labour moving between sectors (for example, Acemoglu and Guerrieri 2008; Ngai and Pissarides 2007).

Duarte and Restuccia (2010) proposed a three-sector model including agriculture, manufacturing and services that allowed both of these structural transformation channels to exist and that was calibrated to US data between 1956 and 2004. Their model was a sequence of static problems, abstracting from household intertemporal choice. They showed that a reallocation of labour could be generated by both channels working in tandem, or, under certain conditions, by either channel in isolation. Studies of structural transformation such as Michaels, Rauch, and Redding (2012), Rogerson (2008) and Gollin, Parente, and Rogerson (2002) have proposed two-sector models by considering the reallocation of labour from agriculture into a combined 'non-agriculture' sector that includes both manufacturing and services. Other studies that developed multi-sector models of structural transformation include Ngai and Pissarides (2007) and Kongsamut, Rebelo, and Xie (2001).

Motor vehicles have not been explicitly considered in these multi-sector general equilibrium models, with labour, land or capital typically included as production inputs and agriculture, manufacturing or services goods available to consumers. To broaden understanding on the relationship between structural transformation and oil prices, Stefanski (2014) proposed a multi-sector, multi-country model that incorporated oil as a production input alongside labour, while Stefanski (2017) included 'modern energy' as an input to production.

It is also important to consider urbanisation in any analysis involving economic development, given a very strong correlation between income per capita and urbanisation among developing countries (Gollin, Jedwab, and Vollrath 2015; Michaels, Rauch, and Redding 2012). Urbanisation has been typically considered as a companion to industrialisation, with historical patterns of cities developing where factories were located. Michaels, Rauch, and Redding (2012) provided empirical evidence in relation to urbanisation in the US between 1880 and 2000 and used a theoretical model to demonstrate the central influence of structural transformation in this process. Their model of structural transformation, including production of an agriculture and a non-agriculture good, was able to predict that only the most densely populated locations produced the non-agriculture good. This was due to a combination of two forces. First, there were weaker agglomeration forces in agriculture than in non-agriculture due to the land-intensive nature of agriculture. Second, a location's population density increased in its productivity, and non-agriculture was characterised by lower mean reversion in productivity (Michaels, Rauch, and Redding 2012).

Furthermore, Brunt and García-Peñalosa (2021) developed a model, calibrated to reflect developments in England between 1550 and 1850, to argue that urbanisation can itself induce structural transformation, with greater innovation and knowledge exchange occurring in denser locations leading to a positive feedback loop between structural change and urbanisation. Using a model calibrated to data on cities in France from 1995 to 2018, Chen et al. (2023) demonstrated that the later structural change from manufacturing to services was more pronounced in cities with higher population density.

Gollin, Jedwab, and Vollrath (2015) presented a three-sector structural transformation model in which urbanisation could also occur in the absence of industrialisation, motivated by a tendency among developing countries to experience high rates of urbanisation in a context of little industrialisation. In addition to industrialisation, their model showed that urbanisation can be driven by increases in income from the exporting of natural resources, known as a 'Dutch disease' or Balassa-Samuelson effect (Gollin, Jedwab, and Vollrath 2015). In their model, rural production consisted only of food, or an agriculture good, while urban production consisted of 'tradeable' and 'non-tradeable' sectors of non-agriculture goods. While the study noted that it was simplistic to simply equate rural production with agriculture and urban production with non-agriculture, it pointed to cross-country empirical evidence from 2000-2010 that non-agriculture accounted for only 30 per cent of rural employment, but 92 per cent of urban employment (Gollin, Jedwab, and Vollrath 2015).

While much of this structural transformation literature has focused on models of a closed economy, structural change can also stem from factors such as international borrowing or trade. To specifically explore these elements, some studies have modelled structural transformation in an open economy (for example, Chen et al. 2023; Cravino and Sotelo 2019; Kehoe, Ruhl, and Steinberg 2018; Świecki 2017; Uy, Yi, and Zhang 2013).

1.3. Environmental Kuznets Curve

This study is also related to literature on the 'Environmental Kuznets Curve' (EKC). This literature stemmed from studies in the early 1970s that began to focus on linking environmental emissions to economic development, such as Forster (1973), Solow (1973) and Stiglitz (1974). Grossman and Krueger (1995) identified a hump shape in emissions per capita over the course of economic development, with emissions increasing during early stages of development but later decreasing. This pattern became known as the EKC, after the Kuznets Curve in inequality due to market forces as an economy develops. Rather than examining emissions per capita as in the standard EKC, several studies have focused on emissions per unit of GDP, or the intensity of emissions, and identified a hump-shaped pattern in intensity during economic development (Stefanski 2013; Bartoletto and Rubio 2008; Tol, Pacala, and Socolow 2006; Kander and Lindmark 2004; Lindmark 2004, 2002).

As part of their study, Copeland and Taylor (2004) conducted a review of EKC literature. They noted four main theoretical explanations for the EKC. First, as the primary source of economic growth changes over time, so too does the impact of this growth on emissions. This possibility was discussed in an empirical analysis by Grossman and Krueger (1995), for example. Second, the EKC arises due to income effects, with demand for environmental quality changing as incomes rise, for example as in López (1994). Third, the pattern is a result of a threshold effect, with either policy being implemented or coming into effect once a certain threshold of emissions is reached. It has been argued that this effect can emerge from either political processes, as in Jones and Manuelli (1995), or opportunities for emissions abatement, as in Stokey (1998). Fourth, increasing returns to abatement have been proposed as an explanation for the EKC, as in Andreoni and Levinson (2001) for example.

However, the existence of the EKC has been disputed in the literature. For example, Stern and Common (2001) presented empirical evidence using a global sample that did not support a common

EKC for sulphur emissions across countries. Other notable criticisms of the EKC literature include Stern (2004) and Carson (2010).

1.4. This study

This research contributes to these strands of literature with an analysis of trends in car use per unit of GDP as an economy develops. The lack of research specifically into car use per unit of GDP, potentially an elementary factor in peak car trends, represents a gap in the literature. From a methodological perspective, there also appears to be a dearth of studies that employ general equilibrium macroeconomic models based on representative agents to analyse peak car trends. Meanwhile, motor vehicles have not previously been explicitly included in general equilibrium models of structural transformation. This study offers a novel perspective on peak car by essentially linking literature on car use and car ownership with literature on general equilibrium models of structural transformation.

In Section 2, I demonstrate that car use per unit of GDP evolves in a hump-shaped pattern over the course of economic development, and that this dynamic stems mostly from the extensive margin, the number of cars per GDP, or car intensity. In other words, as GDP per capita increases, car intensity initially increases sharply before reaching a peak and later decreasing. I then argue that structural transformation can have a fundamental role in producing this relationship. Section 3 develops a model of structural transformation that formalises this argument, and the calibration of this model is described in Section 4.

In Section 5, baseline simulations demonstrate that my model can account for just under a quarter of observed variation in car intensity among a cross section of 54 countries. I conduct counterfactual simulations in Section 6 to demonstrate the role of structural transformation in generating a hump shape in intensity as the economy develops. I find that economies that develop later reach a peak level of car intensity at a later stage, but that this peak occurs at a slightly lower level than that experienced by countries that shifted away from agriculture earlier. I follow up this theoretical approach with a semi-parametric econometric analysis in Section 7 to provide further empirical evidence of the hump-shaped relationship between car intensity and structural transformation. Finally, conclusions from the study are summarised in Section 8.

2. The facts

2.1. Car use per GDP

First, I will demonstrate a hump-shaped relationship between passenger car use per unit of real GDP and real GDP per capita. In other words, as income rises in an economy, car use per GDP increases at first before levelling off and subsequently decreasing. Comparing economies simply using measures such as car use per capita cannot account for the fact that economies produce vastly different levels of GDP. For example, comparing Great Britain and Thailand, two countries with similar population sizes, will reveal substantial differences in car use per capita, but much of this variation would simply reflect differences in GDP. Instead, comparing economies in terms of car use per GDP can offer additional insight on the intrinsic role of car use in economies.

Figure 1 summarises data on distances travelled by passenger car (incorporating both private and commercial cars), measured as PKM, per purchasing power parity (PPP) US dollar (USD) of real GDP from 1970 to 2019 among 26 Organization for Economic Cooperation and Development (OECD) countries in addition to Argentina, Bulgaria and Russia. Data sources and all included countries are detailed in Appendix A.[3] I split country-year pairs into deciles according to real PPP GDP per capita and calculated average levels of car PKM per GDP for each decile. Figure 1 shows a distinct hump shape in the relationship between car PKM per GDP and GDP per capita, with average car PKM per GDP highest in the fourth decile of GDP per capita.

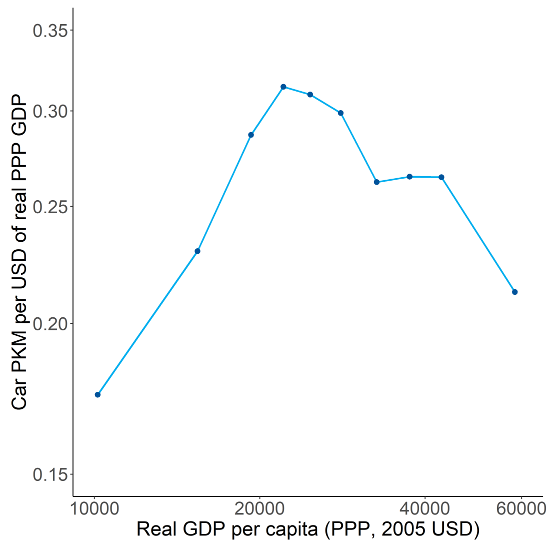


Figure 1: Car passenger kilometres per GDP and real GDP per capita, 29 countries 1970-2019. Axes transformed to $\log_e$ scales. Points show decile averages. Sources: Author's analysis; OECD 2017; Feenstra, Inklaar, and Timmer 2015.

3. These 29 countries are a subset of my 'main panel' for which PKM data was available.

One previous study found the level of car use (measured in VKM) per GDP to be lower in 2005 than in 1995 in 39 out of 42 cities studied across the US, Australia, Canada, Europe and Asia (Kenworthy 2013). The hump shape I show in Figure 1 using data on 29 countries spanning 50 years is a striking pattern that is worth investigating further. Focusing on a single developed economy, I combined data on distance travelled by car[4], measured in VKM in this instance, and the number of licensed private cars from 1950 to 2019 in Great Britain (encompassing England, Scotland and Wales) from the UK Department for Transport (2021b, 2021a) with data from the Penn World Tables on GDP and population (Feenstra, Inklaar, and Timmer 2015). VKM can be decomposed into two components, average VKM per car and the number of registered cars, as follows:

$$VKM = \overline{VKM} \times N_{cars} \tag{1}$$

In Equation 1, $\overline{VKM}$ denotes average VKM per car, while N_{cars} denotes the number of licensed cars. These components could be thought of as intensive ($\overline{VKM}$) and extensive margins (N_{cars}). Both sides of Equation 1 can then be divided by GDP, showing that VKM per unit of GDP can be expressed as the average VKM per car multiplied by the number of licensed cars per unit of GDP as in Equation 2. I will call VKM per GDP 'VKM intensity', and the number of cars per GDP 'car intensity', to highlight them as measures of the level of car use or the number of cars required in the economy to produce one unit of GDP.

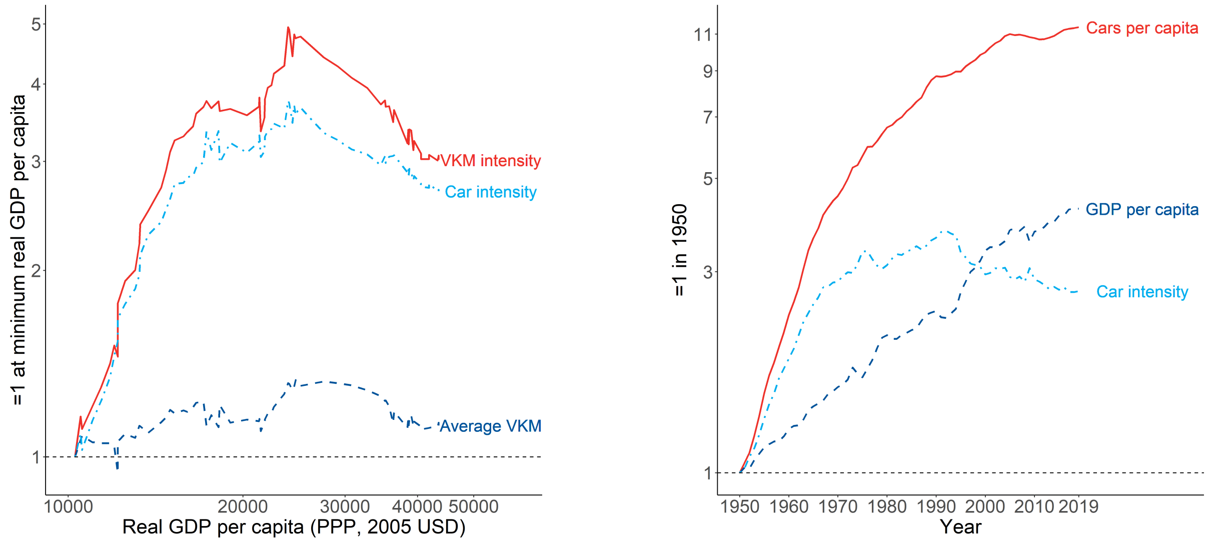
$$\frac{VKM}{GDP} = \overline{VKM} \times \frac{N_{\text{cars}}}{GDP} \tag{2}$$

$$intensity_{\text{VKM}} = \overline{VKM} \times intensity_{\text{car}} \tag{3}$$

Figure 2a plots VKM intensity, average VKM per car and car intensity in Great Britain against real GDP per capita, each normalised to 1 at the minimum (and earliest) level of GDP per capita. First, the plotted VKM intensity line confirms that the hump-shaped pattern identified among a panel of countries in Figure 1 is also evident when analysing a single developed economy. Second, Figure 2a illustrates that the hump shape in the relationship between VKM intensity and GDP per capita derives mainly from the extensive margin, car intensity, with comparatively little change evident in the intensive margin, average VKM per car, during this period. While the extensive margin increased to a peak level that was 3.8 times higher than in 1950, the highest level of the intensive margin over the period was a mere 1.3 times higher than in 1950. This reveals that the bulk of the hump-shaped dynamic derives from the extensive margin. Rather than the average distance travelled by cars changing substantially, it is car intensity that initially increases but then levels off and decreases as income rises. Using survey data,

4. This data series on distance travelled by car also included taxis.

Metz (2010) found that average distance travelled per person had been changing significantly in the UK between 1972 and 2008, although this variable was not limited to car travel. The finding in Figure 2a is consistent with previous research that found VKM to depend heavily on car ownership (Jamroz and Wachnicka 2015; Van Acker and Witlox 2010; De Jong et al. 2004).



(a) VKM intensity decomposition and real GDP per capita. Axes transformed to $\log_e$ scales.

(b) Car intensity decomposition. Y-axis transformed to $\log_e$ scale.

Figure 2: Car VKM intensity and private car intensity, Great Britain 1950-2019. Sources: Author's analysis; UK Department for Transport 2021b, 2021a; Feenstra, Inklaar, and Timmer 2015.

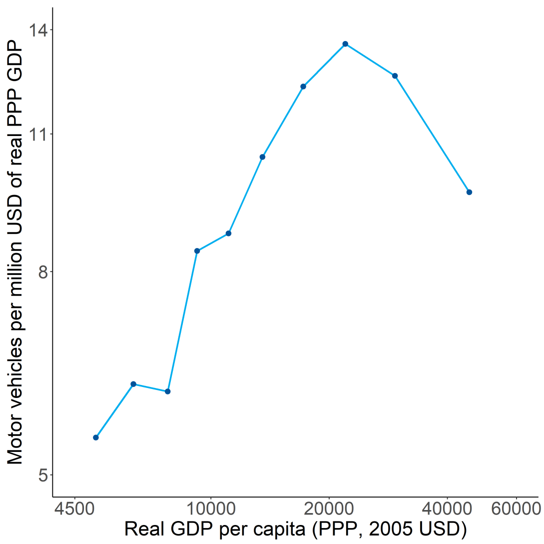
Similarly, car intensity itself can be further decomposed into two per capita components: the number of cars per capita and GDP per capita. Figure 2b shows the evolution of these variables over time in Great Britain, each normalised to 1 in 1950. The dramatic rise in the number of licensed private cars per capita, increasing more than ten-fold over 50 years, is an illustration of the period of 'mass motorisation' that followed the Second World War. During this period in Great Britain, cars were viewed as a marker of affluence and models such as the Mini and Ford Cortina became accessible to a wider population including manual workers (Gunn 2018). The hump shape in car intensity, with a peak level reached in the early 1990s, appears to stem from changes in the rates of increase of cars per capita and GDP per capita.

2.2. Car intensity

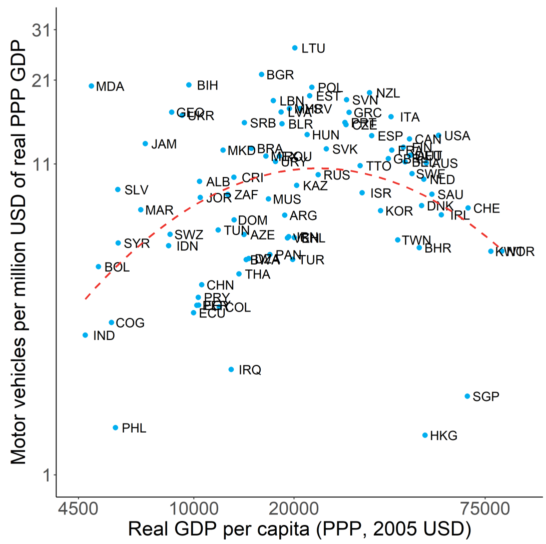
The hump-shaped pattern in private car intensity, shown in Figures 2a and 2b for Great Britain, can also be found among a larger sample of countries. Combining Penn World Table data on GDP and population (Feenstra, Inklaar, and Timmer 2015) with data on the number of private cars in use from Mitchell's *International Historical Statistics* (Palgrave Macmillan Ltd 2013b) for an extended panel of

88 countries over the 1950-2010 period (henceforth referred to as ‘extended panel’), I again split country-year pairs into deciles based on GDP per capita and calculated the average car intensity for each decile.[5] Figure 3a plots this calculated data, revealing a similar hump-shaped pattern with car intensity highest in the eighth decile of GDP per capita. Drawing on a cross section of this 88-country sample, Figure 3b plots car intensity against real GDP per capita in 2010, confirming that a hump-shaped pattern is also reflected in a cross section. I also confirmed that this hump-shaped relationship holds for individual countries in my extended panel in addition to Great Britain (see Appendix A).

These patterns in car intensity across 88 countries for the years 1950-2010 also echo the pattern in PKM per GDP (or PKM intensity) across 29 countries for 1970-2019 shown in Figure 1. This is consistent with the finding in Figure 2a that the hump-shaped pattern in VKM intensity flows mostly from its extensive margin, car intensity.



(a) 1950-2010. Points show decile averages.



(b) 2010. Dashed line shows quadratic regression.

Figure 3: Private car intensity and real GDP per capita, extended panel. Axes transformed to $\log_e$ scales. Sources: Author’s analysis; Feenstra, Inklaar, and Timmer 2015; Palgrave Macmillan Ltd 2013b.

To investigate these car intensity patterns further, I ran the following regression specifications using my extended 88-country panel for the years 1950-2010:

$$intensity_{i,t} = \alpha + \beta_1 real_{i,t} + \beta_2 real_{i,t}^2 + \varepsilon_{i,t} \tag{4}$$

$$intensity_{i,t} = \alpha + \beta_1 real_{i,t} + \beta_2 real_{i,t}^2 + \sum_{i=1}^{M-1} G_i + \varepsilon_{i,t} \tag{5}$$

The outcome variable in both specifications, $intensity_{i,t}$, is private car intensity in country i and year t.

5. The additional countries included in this extended panel, and details of data sources, are outlined in Appendix A.

Both models include real GDP per capita, $real_{i,t}$, in country i and year t and its square as independent variables, while the specification in Equation 5 additionally includes country fixed effects. These fixed effects control for time-constant, country-specific factors that may be influencing car intensity. I also clustered standard errors at the country level in all three specifications, allowing for possible correlations between a country's error terms. If there is a hump-shaped relationship between car intensity and GDP per capita, that is independent of fixed country effects in the case of Equation 5, the β_1 coefficient would be positive and the β_2 coefficient negative.

Table 1: Private motor vehicles per GDP and real GDP per capita in extended panel 1950-2010

	(1)	(2)	(3)
Real GDP per capita	0.478***	0.398***	0.346***
	(0.091)	(0.081)	(0.100)
Squared real GDP per capita	-0.007***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)
Observations	2998	2998	88
Adjusted R^2	0.151	0.165	0.106
Fixed effects	No	Yes	No

Standard errors in parentheses
Standard errors clustered at country level
Within R-squared reported for fixed effects regression
Real GDP per capita in thousand 2005 PPP USD
Sources: Author's analysis; Feenstra, Inklaar, and Timmer 2015; Palgrave Macmillan Ltd 2013b
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results for these regressions are presented in Table 1. Columns 1 and 2 show regression coefficients for Equations 4 and 5 respectively when employing all available country-year pairs across the extended panel of 88 countries for the 1950-2010 period, while column 3 shows coefficients for Equation 4 run on a 2010 cross section. In all three models, including the fixed effects model (column 2), car intensity is indeed positively associated with GDP per capita and negatively associated with the square of GDP per capita. This signifies a hump-shaped relationship between car intensity and real GDP per capita that is independent of time-constant, country-specific factors.

These facts indicate that as GDP per capita rises, the level of private car intensity in the economy initially increases before peaking and subsequently decreasing. This implies that as countries reach high levels of economic development, they become less car-dependent, with fewer cars required for each unit of GDP produced. We could also infer from these patterns among developed countries that countries at earlier stages of development may be expected to become more car dependent in the short term, but to experience a decrease in car intensity in the longer run as they continue to develop.

2.3. Carbon emissions intensity

I opened this paper by highlighting the key role of the transport sector in carbon dioxide emissions. Therefore, it is worth considering what these patterns in private car intensity imply for the intensity of carbon dioxide emissions, or emissions per unit of GDP. Linking estimates of total carbon emissions deriving from all fuel combustion from the International Energy Agency (IEA 2022c) with data on real GDP per capita (Feenstra, Inklaar, and Timmer 2015) for my extended panel between 1971 and 2019, I again separated country-year pairs into deciles based on GDP per capita and calculated the average emissions intensity for each decile. Figure 4 plots this data, essentially revealing the latter stages of a hump shape. This is consistent with the hump shape shown in car intensity (Figure 3a), and a peak level of emissions intensity occurring at a lower level of GDP per capita than the peak level of car intensity reflects the separate dynamic of increasing fuel efficiency in motor vehicles over time.

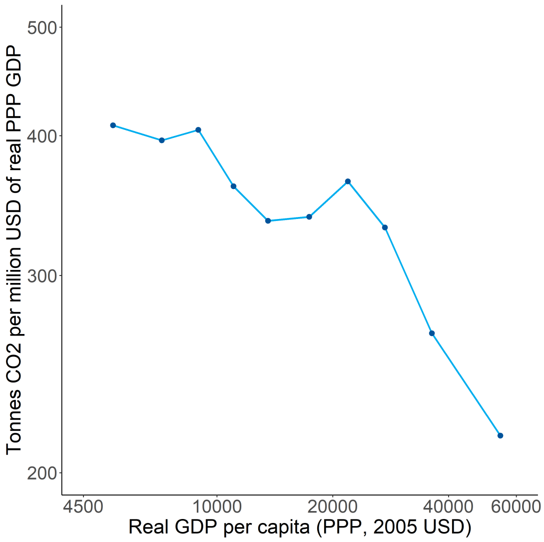


Figure 4: Carbon emissions intensity and real GDP per capita, extended panel 1971-2019. Axes transformed to $\log_e$ scales. Points show decile averages. Sources: Author's analysis; IEA 2022c; Feenstra, Inklaar, and Timmer 2015.

2.4. Explaining these facts

I have shown that a hump-shaped relationship between the intensity of private car use (VKM intensity) and GDP per capita mainly stems from the extensive margin, highlighting the number of private cars per GDP (car intensity) as the key variable of interest. Could these patterns in private car intensity be explained by developed economies having reached a saturation level of car ownership (Tanner 1978)? That some level of saturation in car ownership exists seems plausible. However, exactly what this level is remains unclear. Figure 5 plots the peak number of private cars per capita among countries that had reached such a peak before 2010 and reveals a wide range in these peak levels, for example 0.25 cars per person in Taiwan compared with 0.79 cars per person in the US. In addition, decreases in car ownership among younger cohorts (Melia, Chatterjee, and Stokes 2018; Delbosc and Currie 2013; Kuhnimhof et al. 2012) occurring alongside increases among older adults (Kuhnimhof, Zumkeller, and Chlond 2013) point to a more complicated picture than there simply being an underlying level of saturation. The wide range between countries depicted in Figure 5 suggests that while saturated car ownership may be a factor in hump-shaped car intensity patterns, there were also other elements involved.

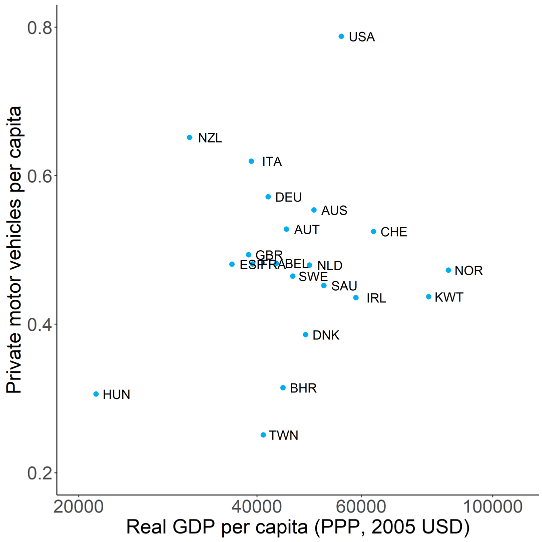
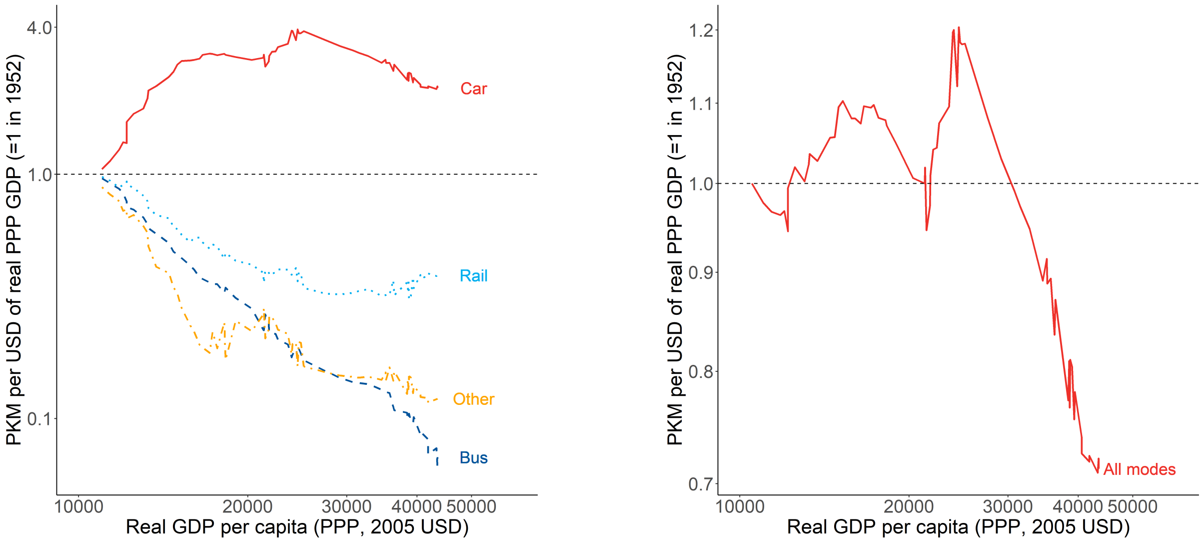


Figure 5: Peak level of private cars per capita and real GDP per capita, extended panel 1950-2010. X-axis transformed to $\log_e$ scale. Sample limited to countries with GDP per capita >20,000 PPP USD and where annual growth levels of vehicles per capita were below 2 per cent in each of the final 3 years of the sample period. Source: Feenstra, Inklaar, and Timmer 2015; Palgrave Macmillan Ltd 2013b.

Alternatively, could these car intensity patterns be simply explained by shifts to public transport (Newman, Kenworthy, and Glazebrook 2013)? Descriptive statistics of passenger transport from the UK Department for Transport (2013) suggest that this is not the case. Figure 6a plots the level of PKM intensity by passenger transport mode against GDP per capita in Great Britain from 1952 to 2019, with each mode normalised to 1 in 1952. This shows that while there appears to be a minor recovery in rail's PKM intensity in recent years, which would be consistent with findings by Newman, Kenworthy, and Glazebrook (2013), the PKM intensity of other modes have continued to decrease and that the PKM intensity of each mode other than the car remains substantially lower in 2019 than in 1952.

It is also worth pointing out that since the period of mass motorisation, the share of total PKM accounted for by cars has been overwhelmingly large, peaking at 86.9 per cent in 1994 and only reducing to 84.5 per cent by 2019 (UK Department for Transport 2013). As a result of this, plotting total PKM intensity of all passenger transport modes against GDP per capita also produces a hump-shaped pattern in intensity, as depicted in Figure 6b. Based on this evidence, a shift to public transport alone cannot explain these car intensity patterns.



(a) PKM per GDP by transport mode.

(b) Total PKM per GDP.

Figure 6: PKM per GDP across all transport modes and real GDP per capita, Great Britain 1952-2019. Axes transformed to $\log_e$ scales. Source: Author's analysis; Feenstra, Inklaar, and Timmer 2015; UK Department for Transport 2013.

What about road fuel prices (Bastian, Börjesson, and Eliasson 2016; Bastian and Börjesson 2015; Grimal, Collet, and Madre 2013)? Figure 7 displays typical retail prices for petrol and diesel along with private car intensity in the UK for the 1955-2010 period. Road fuel prices, which constitute a significant portion of the running costs of motor vehicles, were substantially higher in 2010 than they were at the height of mass motorisation in 1955 in the UK, and this must be regarded as a factor in peak car trends as highlighted by Bastian, Börjesson, and Eliasson (2016), Bastian and Börjesson (2015) and Grimal, Collet, and Madre (2013). However, Figure 7 is also consistent with the argument of Puentes and Tomer (2008), Metz (2010), Newman and Kenworthy (2011) and Millard-Ball and Schipper (2011), in that car intensity appeared to be levelling off in the UK prior to the major spikes in fuel prices associated with the 1973 oil crisis. This suggests that while higher fuel prices must be considered to have contributed to the hump shape in car intensity, they are not the whole story either.

More recently, the COVID-19 pandemic led to increases in remote working (Brynjolfsson et al. 2020), and this change in commuting patterns may have affected levels of car intensity. However, as all observed data shown in this study is from before 2020, the hump-shaped relationship between car intensity and GDP per capita also pre-dates the COVID-19 pandemic.

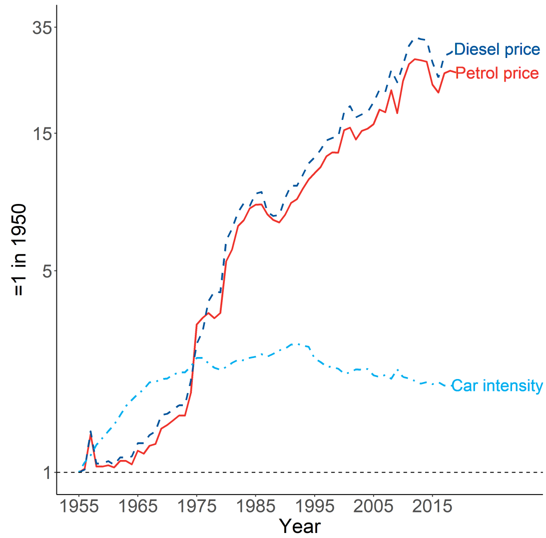


Figure 7: Private cars per GDP, road fuel prices and real GDP per capita, Great Britain 1955-2010. Y-axis transformed to $\log_e$ scale. Road fuel prices are typical January retail prices in current pence per litre, indexed relative to 1955. Petrol price is for lead replacement petrol 1955-1988, and premium unleaded petrol 1989-2010. Source: Author's analysis; UK Department for Energy Security and Net Zero 2023b; Feenstra, Inklaar, and Timmer 2015; Palgrave Macmillan Ltd 2013b.

2.5. Structural transformation

How else could we explain this hump-shaped pattern in car intensity? In this paper, I argue that as a country develops, a systematic change in car intensity occurs because of structural transformation, the reallocation of economic activity between broad sectors. Consider a fictional economy and its experience of economic development. When the economy is in its infancy in terms of development, it is dominated by an agriculture sector that is characterised by traditional and labour-intensive processes. At this stage, agriculture is highly localised with households and communities growing and consuming their own food, and the production of these agriculture goods provides the bulk of employment. These early beginnings are therefore marked by a low level of car intensity.

As the economy grows, technological improvements such as better drainage and systems of crop rotation increase the productivity of labour in the agriculture sector. Moreover, individuals and communities begin to specialise and trade with each other, leading to a relative increase in car intensity in the agriculture sector. As this is happening, the economy is also experiencing a seismic change as it gradually re-orientates itself towards a non-agriculture sector. Initially, this change can be described as industrialisation as the non-agriculture sector may initially be largely comprised of more car-intensive industry and manufacturing sub-sectors. These sectors would require workers to commute to factory locations rather than work locally as was the case in the early, traditional agriculture sector. This industrialisation can also be associated with a process of urbanisation. For example, Gollin, Jedwab, and Vollrath (2015) defined urbanisation in their model economy as an increasing labour share in non-agriculture sectors. The increasing car intensity in agriculture, coupled with the broader shift of economic activity towards the more car-intensive non-agriculture sector, gives rise to a substantial increase in aggregate car intensity in the economy.

Later, as the economy continues to mature and industrialisation is completed, the non-agriculture sector takes the place of agriculture as the dominant sector in the economy. As this occurs, however, non-agriculture itself may shift towards services, and this could facilitate a reduction in its sectoral car intensity if the production of services employs cars less intensively than industry and manufacturing. In addition, industry and manufacturing sectors within non-agriculture may themselves become more efficient in the use of cars as the economy develops, the population becomes more urbanised and technology improves, and this could further contribute to a decrease in non-agriculture's car intensity. Due to the now-pivotal role of non-agriculture within the economy, this decrease in its sectoral intensity would be expected to propel aggregate car intensity in the economy downwards, following the sharp increase in intensity during the earlier stages of development. A similar theory to this based on dynamic sectoral oil intensities was proposed by Stefanski (2014) in exploring the effect of structural transformation on oil prices. This argument can also be considered distantly related to the growth source explanation for the EKC (Copeland and Taylor 2004; Grossman and Krueger 1995).

To explore this theory in relation to car intensity, I collated a panel dataset of 54 countries over the 1995-2016 period (henceforth referred to as 'main panel') to assess changes in sectoral motor vehicle intensity over the structural transformation process. Based on data availability, this main panel included 34 OECD members, 5 countries designated by the OECD as 'key partners', and 15 non-members. This data was sourced from OECD Input-Output Tables (OECD 2021), the United Nations (UN) national accounts main aggregates database (UN 2021a), International Labour Organization (ILO) modelled employment estimates (ILO 2020), and the Penn World Tables (Feenstra, Inklaar, and Timmer 2015). Further details of these data sources and how I collated them are outlined in Appendix A.

I used data from the OECD Input-Output Tables (OECD 2021) to measure the value of sectoral motor vehicle inputs to production. These tables include a category of inputs labelled 'manufacture of motor vehicle, trailers and semi-trailers' (division 29), which I employed when calculating the share of sectoral value added attributable to car transport. More disaggregated data would naturally be more useful in the context of this study, as inputs from division 29 incorporate the manufacture of commercial motor vehicles and trailers in addition to private cars. Separately, however, I decomposed total motor vehicle intensity in Great Britain over the 1950-2010 period into private car intensity and commercial vehicle intensity, and found that the hump-shaped pattern can also be found when plotting the combined intensity of all motor vehicles against GDP per capita (see Appendix A). I also confirmed that the hump-shaped pattern in intensity could be found using aggregate motor vehicle inputs per GDP, calculated using Input-Output data (OECD 2021) data (see Appendix A).

To measure structural transformation, I relied on the share of total employment accounted for by the agriculture sector using ILO (2020) data. Figure 8a illustrates the well-documented process of structural transformation (for example, see Herrendorf, Rogerson, and Valentinyi 2014; Rogerson 2008; Kuznets 1973), where among the 54 countries included in my main panel, the share of total employment in the agriculture sector was lower in countries with a higher level of GDP per capita. This shows that the agriculture labour share can be considered a measure of a country's structural transformation.

Using my collated main panel, I ran the following linear regression separately for the agriculture sector and for the 'non-agriculture' sector (an aggregation of all other sectors other than the transport sector):

$$VehInputs_{i,t} = \alpha + \beta AgriLabour_{i,t} + \varepsilon_{i,t} \tag{6}$$

In Equation 6, the dependent variable $VehInputs_{i,t}$ measures the share of sectoral value added (with value added measured in constant 2005 PPP USD) in country i in year t that is accounted for by motor vehicle inputs. The independent variable $AgriLabour_{i,t}$ represents the share of total employment in agriculture in country i and year t. This regression essentially relates sectoral motor vehicle intensity to the extent of structural transformation in each country over time, with the coefficient of interest β capturing the linear relationship between sectoral vehicle intensity and structural transformation.

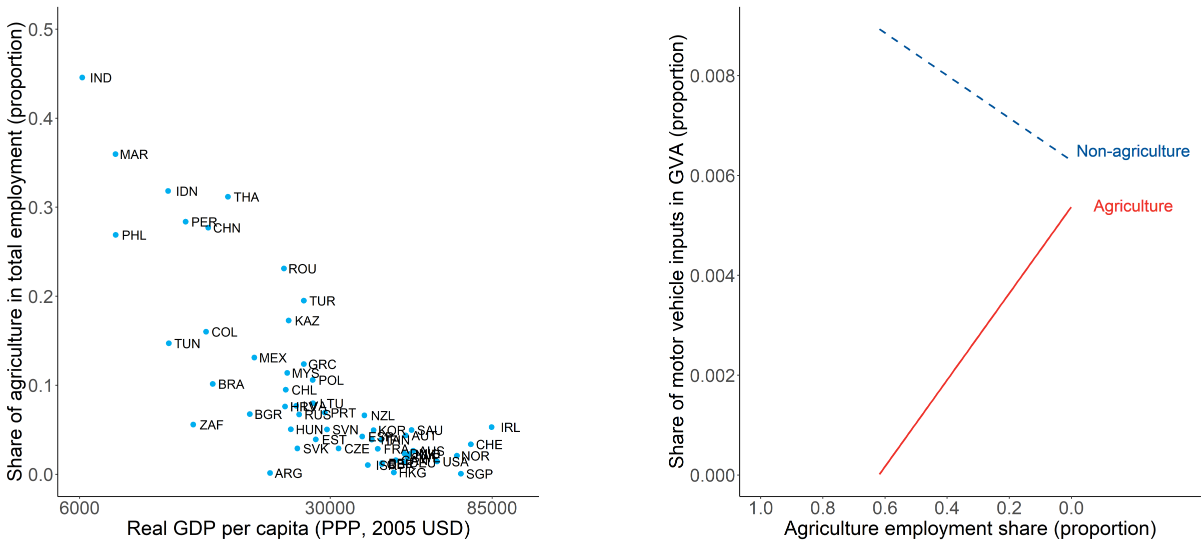
Table 2 presents results of this regression for agriculture (see column 1) and non-agriculture (see column 2). Since the agriculture labour share decreases during the process of structural transformation, Figure 8b depicts regression lines for each of these specifications with the x-axis reversed and extended over the full domain of the agriculture labour share to illustrate progress in structural transformation.

Table 2: Changes in sectoral motor vehicle inputs over process of structural transformation for main panel 1995-2016

	(1) Agriculture	(2) Non-agriculture
Agriculture labour share	-0.009***	0.004***
	(0.001)	(0.001)
Observations	1188	1188
Adjusted R^2	0.031	0.009

Standard errors in parentheses
Sources: Author's analysis; OECD 2021; ILO 2020; Feenstra, Inklaar, and Timmer 2015
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 reveals a negative coefficient on the agriculture labour share variable in the agriculture sector regression, indicating that a higher share of total employment in agriculture was associated with a lower



(a) Agriculture employment shares and real GDP per capita, 2016. X-axis transformed to $\log_e$ scale.

(b) Regression lines, 1995-2016. X-axis extended over full domain and reversed for illustration.

Figure 8: Changes in sectoral motor vehicle intensity over structural transformation, main panel. Sources: Author's analysis; OECD 2021; ILO 2020; Feenstra, Inklaar, and Timmer 2015.

share of transport inputs in the value added of the agriculture sector. In other words, as structural transformation progressed and the agriculture labour share reduced, more motor vehicle transport was required in agriculture to produce one unit of output, as summarised in Figure 8b. Intuitively, this can be explained by traditional, localised agriculture processes making way for modern, more car-intensive agriculture processes.

Conversely, a positive coefficient was found on the agriculture labour share variable in the non-agriculture regression. As illustrated in Figure 8b, this suggests that over the course of structural transformation, less motor vehicle transport was needed to produce one unit of non-agriculture output. This also makes intuitive sense, as this sector may have started life as a transport-intensive sector based on industry and manufacturing, but later morphed into a relatively less intensive sector characterised by an increasingly efficient services sector.[6]

These processes could be fundamental to producing a hump-shaped pattern in aggregate car intensity as a country develops. The aggregate car intensity of the economy is essentially a weighted average of sectoral car intensities. During the early stages of the structural transformation process, the economy is beginning to shift from agriculture to a considerably more car-intensive non-agriculture sector, thus increasing aggregate intensity. However, this non-agriculture sector is gradually becoming less car-intensive over time, which would lead to a decrease in aggregate car intensity as the sector comes to

6. I also ran these regressions separately for the industry and services sectors, and found a positive coefficient on the agriculture labour share in the services regression, while the corresponding coefficient was not significantly different to 0 in the industry regression (see Appendix B).

dominate the maturing economy.

Clearly, that this process of structural transformation could produce a hump-shaped pattern in aggregate car intensity over the course of economic development is dependent on underlying parameters in the economy. How quickly does the structural transformation into non-agriculture occur? What is the rate of decrease in non-agriculture's sectoral car intensity? To help explore this, I developed and calibrated a theoretical model of structural transformation from agriculture to non-agriculture to show that a two-sector model could produce a hump-shaped pattern in car intensity, but that a one-sector model could not do so due to the absence of any structural transformation. I describe this model in the following section.

3. The model

This simplified general equilibrium model of structural transformation represents a mathematical formalisation of my theory of why we observe a hump-shaped pattern in car intensity in the real world. I treat this closed economy model as a sequence of static problems that vary over time only via exogenous changes in the productivity of firms. This approach, which abstracts from intertemporal choice, has previously been adopted in studies of structural transformation such as Stefanski (2014) and Duarte and Restuccia (2010). I will describe this model for a single period and thus omit a time subscript t for simplicity. Additional theory in relation to the model is outlined in Appendix C.

3.1. Consumers

This model economy consists of representative consumers and firms interacting with each other in a perfectly competitive market. The representative household decides on its consumption levels, c_s, of the two final goods: an agriculture good $s = A$ and a composite non-agriculture good $s = N$. As in Stone-Geary preferences, I assume that there exists a subsistence level of the agriculture good, denoted by $\overline{c_A}$, such that the household will devote all of its income to consuming this good until $\overline{c_A}$ is reached. Intuitively, the household requires $\overline{c_A}$ of the agriculture good, which can be thought of as food, to survive and will thus spend all of its budget on this good until it has acquired $\overline{c_A}$.

The household takes the wage rate w and prices p_s in the economy as exogenously given and seeks to maximise its utility from consuming these two goods subject to a budget constraint. I assume this consumer optimisation problem takes the form of a log utility function:

$$\begin{aligned} \max_{c_A, c_N} \quad & \phi \log(c_A - \overline{c_A}) + (1 - \phi) \log(c_N) \\ \text{s.t.} \quad & p_A c_A + p_N c_N = w \end{aligned} \tag{7}$$

In this constrained maximisation problem, $\phi \in (0,1)$ represents the utility weight on the agriculture good. The subsistence level of the agriculture good is given by $\overline{c_A} > 0$.

3.2. Firms

Meanwhile, production in the model takes place across three perfectly competitive sectors $s = A, N, M$: sector A producing the final agriculture good, sector N producing the final non-agriculture good, and sector M producing motor vehicles as an intermediate good. Motor vehicles thus appear in my model as an intermediate good that is used as an input in the production of the final goods sectors A and N alongside labour. The price of motor vehicles in the model, p_M, is a variable cost that can be thought of as the leasing cost of a single vehicle that implicitly combines both variable operating costs, such as fuel, and fixed costs in a single variable figure. As a simplification, the model abstracts away from any explicit fixed costs, and does not incorporate possible alternatives to motor vehicles such as public transport.

The firms take the wage rate w and prices p_s in the economy as exogenously given and select levels of motor vehicle and labour inputs, M_s and L_s, that maximise profits Π_s. I assume the sector-specific firm profit maximisation problems for the agriculture and non-agriculture sectors A and N both take the form of a constant elasticity of substitution function:

$$\max_{M_s, L_s} p_s B_s \left(\eta_s M_s^{\frac{\sigma_s - 1}{\sigma_s}} + (1 - \eta_s) L_s^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} - p_M M_s - w L_s, \quad s = A, N \tag{8}$$

In this maximisation problem, total factor productivity B_s differs between the two sectors. Similar to Duarte and Restuccia (2010), Stefanski (2014) and Gollin, Jedwab, and Vollrath (2015), this parameter captures labour productivity in addition to any effects of capital or land in production. Differences in labour productivity across countries and over time can stem from factors such as endowments and capital intensity. However, my model follows the approach of Duarte and Restuccia (2010) in abstracting from these factors as the focus is not explicitly on the productivity of labour.

The parameter η_s is the sector-specific motor vehicle share parameter, while σ_s represents the sector-specific elasticity of substitution between motor vehicle and labour inputs. This elasticity of substitution measures how easy it is for the firm to switch between motor vehicles and labour in production. Formally, it is defined as the percentage change in the firm's marginal rate of technical substitution due to a 1 per cent change in the ratio of motor vehicles to labour inputs, $\frac{M_s}{L_s}$, holding the level of output constant. A positive elasticity between two factors of production indicates that the factors have some degree of substitutability, and lower values of elasticity are associated with factors of production that are more difficult to swap for each other. In the extreme case, perfect substitutes have an elasticity of infinite.

A constant elasticity of substitution production function is a special case in which the elasticity is simplified to be constant for any combination of production inputs.[7] The two-factor constant elasticity of substitution production function was first employed by Solow (1956) before becoming widespread in economic literature. As I will discuss later, these constant sectoral elasticities play a significant role in determining the evolution of motor vehicle intensity within sectors over time.

In this model economy, I assume labour can freely move between sectors and thus equalise wage rates to produce a common economy-wide wage rate w. Similarly, I assume motor vehicles produced by firms in sector M can be used in the production of both final goods at a common cost p_M.

An input demand function for M_s in terms of L_s can then be derived from the first-order conditions of this maximisation problem (see Appendix C) and solving for M_s:

$$M_s = \left(\frac{w}{p_M}\right)^{\sigma_s} \left(\frac{\eta_s}{1-\eta_s}\right)^{\sigma_s} L_s, \quad s = A, N \tag{9}$$

Meanwhile, I assume the firm profit maximisation problem for the intermediate motor vehicle sector M takes a linear form:

$$\max_{L_M} p_M B_M L_M - w L_M \tag{10}$$

In this sector, a representative firm operating in perfect competition takes the economy-wide wage rate w and the price of a motor vehicle p_M as exogenously given and chooses a level of labour inputs L_M in order to maximise profit Π_M. Total factor productivity in this sector is given by B_M.

It should be noted that some model simulations involved extending the model backwards to a period before structural transformation began, where the non-agriculture labour share was 0. For these periods, I assumed that the model economy consisted only of a traditional agriculture sector that used labour as the sole production input. Car intensity in my model economy thus remained at 0 during this period until structural transformation began.

3.3. Carbon emissions

The use of motor vehicle inputs pollutes the environment in my model economy. Specifically, the deployment of M_s motor vehicles produces P_s units of carbon emissions as follows:

$$P_s = \rho M_s, \quad s = A, N \tag{11}$$

7. A further simplification of this production function that is common in economic literature is the case where this constant elasticity of substitution is unitary, known as the Cobb-Douglas production function. I do not rely on Cobb-Douglas production in my model so that while the elasticity of substitution is constant within sectors, I can allow it to differ between sectors.

In Equation 11, the parameter ρ represents the economy-wide emissions factor of motor vehicles. I assume that this parameter is exogenously changing over time to reflect developments in the fuel efficiency of motor vehicles. These emissions are simply a side effect of production, and do not affect the utility of consumers or the productivity of firms in my model economy. This is a fair characterisation of pollution, as it is typically regarded as a negative externality and individual concerns in relation to carbon emissions and global warming deriving from consumption are a relatively recent phenomenon.

3.4. Competitive equilibrium

The competitive equilibrium in this model consists of: final goods prices $\{p_A, p_N\}$, taken as exogenous by consumers and firms; a common wage rate w and motor vehicle p_M, also taken as exogenous by agents; a consumption bundle $\{c_A, c_N\}$, chosen by the representative household to maximise utility subject to its budget constraint, given final goods prices and the wage rate; labour $\{L_A, L_N, L_M\}$ and motor vehicle $\{M_A, M_N\}$ inputs, set by the representative firms to maximise profits given final goods prices, the common wage rate and motor vehicle cost; and consequent levels of final output $\{Y_A, Y_N\}$, based on the chosen inputs and sector-specific productivity.

I specify four market-clearing conditions for the economy to satisfy to reach this competitive equilibrium. First, the labour market clears such that all labour provided by the household is split between the three goods sectors: $L = L_A + L_N + L_M$. Second, the market for motor vehicles clears such that all vehicles produced by the firm in sector M are split between the two final goods sectors as production inputs: $B_M L_M = Y_M = M_A + M_N$. Finally, both final goods markets clear such that output in each sector equals the quantity demanded: $Y_A = c_A L$ and $Y_N = c_N L$.

3.5. Characterisation

The first step in characterising this model is to normalise the price of one good to 1. This good acts as the 'numeraire' in the model, and all other good prices and the wage rate are then relative to the numeraire. I choose motor vehicles for this task, so I set $p_M = 1$. This means that the first order condition of the motor vehicle firm's maximisation problem (see Appendix C) can be rewritten as $w = B_M$, showing that the wage rate in my model economy is equal to the level of total factor productivity in the motor vehicle sector. Armed with this fact, Equation 9 can be rewritten as follows:

$$M_s = B_M^{\sigma_s} \left(\frac{\eta_s}{1 - \eta_s} \right)^{\sigma_s} L_s, \quad s = A, N \tag{12}$$

This can then be substituted into the second of the firm first-order conditions (see Appendix C), giving an equation which in turn can be simplified and solved for p_s to give the price of each the agriculture and non-agriculture goods in terms of model parameters:

$$p_s = \frac{B_M^{\frac{\sigma_s}{\sigma_s - 1}}}{B_s} (\eta_s^{\sigma_s} B_M^{\sigma_s} + (1-\eta_s)^{\sigma_s} B_M)^{\frac{1}{1-\sigma_s}}, \quad s = A, N \tag{13}$$

Equation 13 for each $s = A$ and $s = N$ can then be substituted into the respective consumer demand functions (see Appendix C) to express the functions in terms of model parameters:

$$c_A = \phi B_A B_M^{\frac{1}{1-\sigma_A}} (\eta_A^{\sigma_A} B_M^{\sigma_A} + (1-\eta_A)^{\sigma_A} B_M)^{\frac{1}{\sigma_A - 1}} + (1-\phi)\overline{c_A} \tag{14}$$

$$\begin{aligned} c_N =& B_N B_M^{\frac{-\sigma_N}{\sigma_N - 1}} \left(B_M - \frac{B_M^{\frac{\sigma_A}{\sigma_A - 1}}}{B_A} \overline{c_A} (\eta_A^{\sigma_A} B_M^{\sigma_A} + (1-\eta_A)^{\sigma_A} B_M)^{\frac{1}{1-\sigma_A}} \right) ... \\ & ...(\eta_N^{\sigma_N} B_M^{\sigma_N} + (1-\eta_N)^{\sigma_N} B_M)^{\frac{1}{\sigma_N - 1}} (1-\phi) \end{aligned} \tag{15}$$

Finally, to identify the sectoral labour inputs L_A, L_N and L_M analytically, equations 12, 13, 14 and 15 can be substituted into the market clearing equations and solved for each L_A, L_N and L_M.

3.6. Model discussion

3.6.1. Structural transformation

In my model, structural transformation in the form of a shift in labour from the agriculture to the non-agriculture sector is generated by an income effect stemming from non-homothetic preferences, which is the demand approach of the two broad techniques in the literature identified by Herrendorf, Rogerson, and Valentinyi (2014) and Rogerson (2008). Due to the agriculture good in my model having a Stone-Geary subsistence level, $\overline{c_A}$, the share of expenditure devoted to the agriculture good can be shown to be decreasing in income w:

$$\frac{p_A c_A}{w} = \phi + (1-\phi)\frac{p_A \overline{c_A}}{w} \tag{16}$$

This implies an income elasticity of less than one for the agriculture good: as income rises, consumers will spend a lower proportion of their income on the agriculture good and increasingly favour the non-agriculture good. The result of this dynamic is a shift in labour from agriculture to non-agriculture to meet this increase in demand as income rises.

3.6.2. Urbanisation

Michaels, Rauch, and Redding (2012) presented a model demonstrating the key role of structural transformation in generating urbanisation. Based on this, similar to the approach of Gollin, Jedwab, and Vollrath (2015), I assume that the agriculture good is produced only in rural locations, while the non-agriculture goods is produced only in urban locations, and that goods can be traded freely between locations. This is essentially a reduced-form way of modelling the relationship between structural transformation and urbanisation that was more comprehensively modelled by Michaels, Rauch, and Redding (2012). Based on this, urbanisation in my model corresponds with the increase in labour in the non-agriculture sector.

3.6.3. Motor vehicle intensity

I am interested in car intensity in this study, or in my model, motor vehicle intensity. Motor vehicle intensity is given by the total value of vehicle inputs, $p_M M_A + p_M M_N$ divided by the total value of final goods, $p_A Y_A + p_N Y_N$, which can be simplified to the following:

$$\frac{p_M M_A + p_M M_N}{p_A Y_A + p_N Y_N} = \left(\frac{\eta_A}{1-\eta_A}\right)^{\sigma_A} B_M^{\sigma_A - 1} \frac{L_A}{L} + \left(\frac{\eta_N}{1-\eta_N}\right)^{\sigma_N} B_M^{\sigma_N - 1} \frac{L_N}{L} \tag{17}$$

Equation 17 shows that aggregate motor vehicle intensity in the economy is essentially a weighted average of sectoral intensities. As labour shifts from agriculture to non-agriculture during structural transformation, with $\frac{L_N}{L}$ increasing at the expense of $\frac{L_A}{L}$, the weight of the non-agriculture sector in aggregate intensity becomes larger. Equation 17 also highlights the central role played by the sectoral elasticities of substitution, σ_s for $s = A, N$, in this intensity. During the structural transformation process in my model, total factor productivity in the motor vehicle sector, B_M, is exogenously increasing. As shown in Equation 17, the impact of this dynamic on aggregate intensity is dependent on these elasticities. Different sectoral elasticities mean the aggregate elasticity of substitution across the whole economy will be endogenously shifting during structural transformation, and this is a key mechanism in generating aggregate intensity patterns.

I illustrated in Table 2 and Figure 8b that motor vehicle intensity has been increasing in agriculture but decreasing in non-agriculture among my main panel of countries. In my model, agriculture and non-agriculture sectoral motor vehicle intensities (in current prices for illustration) can also be expressed as follows:

$$\frac{p_M M_s}{w L_s} = \frac{\eta_s}{1-\eta_s} \left(\frac{M_s}{L_s}\right)^{\frac{\sigma_s - 1}{\sigma_s}}, \quad s = A, N \tag{18}$$

Equation 18 further emphasises the fact that the sector-specific elasticities of substitution between vehicle and labour inputs, σ_s for $s = A, N$, are key in determining sectoral motor vehicle intensity over time. For example, if the vehicle-labour ratio $\frac{M_s}{L_s}$ was increasing over time, an elasticity of substitution that is greater than 1 in agriculture and less than 1 in non-agriculture, $\sigma_A > 1$ and $\sigma_N < 1$, would produce the increasing motor vehicle intensity in agriculture and decreasing intensity in non-agriculture as observed. Conversely, setting $\sigma_A < 1$ and $\sigma_N > 1$ would produce these patterns if the vehicle-labour ratio was decreasing over time. Considering the number of registered cars per capita in an economy as an estimate of the aggregate motor vehicle-labour ratio, the substantial increase over time in cars per capita in Great Britain shown in Figure 2b suggests that $\frac{M_s}{L_s}$ has most likely been increasing. This indicates that when calibrating the model, the elasticities of substitution should be set at $\sigma_A > 1$ and $\sigma_N < 1$, which I confirm in the following section.

4. Model calibration

I calibrated my model to data aggregated across my main country panel between 1995 and 2016. This involved setting model parameters such that the model matches key features of structural transformation and sector-specific use of motor vehicle inputs across these countries during this period. I essentially treated the 54 countries in my main panel as a single large economy, and therefore abstracted away from international trade between countries. As my model economy is closed to international trade for simplicity, calibrating the model to the trends observed in this aggregate data had the benefit of reducing any influence of international trade on these trends. In addition, while individual countries in the panel completed the process of structural transformation from agriculture to non-agriculture much earlier than 1995, when considering the aggregated data, the agriculture labour share decreased steadily from 39.0 per cent in 1995 to 23.8 per cent in 2016. The aggregate data, therefore, provided a useful reference for a structural transformation out of agriculture over a period of 22 years. Details on all data sources and the construction of variables are provided in Appendix A.

Using ILO (2020) data, I normalized the size of the labour force to 1 in 1995, and calculated the annualised growth rate of the labour force between 1995 and 2016.

For sectoral total factor productivity, I calculated gross value added (GVA) per worker in constant 2005 USD for the agriculture, non-agriculture (excluding transport) and transport sectors using United Nations (UN) data (UN 2021a). I then normalised each sector to 1 in 1995 and calculated sector-specific annualised growth rates. In the absence of more disaggregated data, I employed GVA per worker in the transport sector as a proxy for total factor productivity in my motor vehicle sector.

Similarly, for the economy wide motor vehicle emissions factor, I calculated the average carbon emissions from motor gasoline combustion (excluding biofuels) on roads per private motor vehicle using IEA (2022c) and Palgrave Macmillan Ltd (2013b) data across my main panel for each year. I then normalised this factor to 1 in 1995, and calculated the annualised growth rate to 2016.

Next, I calibrated sector-specific motor vehicle-labour elasticities of substitution σ_A and σ_N, and sector-specific motor vehicle share parameters η_A and η_N. First, Equation 9 can be rearranged as a ratio of motor vehicle to labour inputs for the agriculture and non-agriculture sectors:

$$\frac{M_s}{L_s} = \left(\frac{\eta_s}{1-\eta_s}\right)^{\sigma_s} \left(\frac{w}{p_M}\right)^{\sigma_s}, \quad s = A, N \tag{19}$$

The log of Equation 19 is:

$$\log\left(\frac{M_s}{L_s}\right) = \sigma_s \log\left(\frac{\eta_s}{1-\eta_s}\right) + \sigma_s \log\left(\frac{w}{p_M}\right), \quad s = A, N \tag{20}$$

Using sectoral input data from the OECD (2021) and ILO (2020) data on employment, I filled in values for M_A, L_A, w and p_M for 2016 and then estimated Equation 20 as a regression using ordinary least squares (OLS). As the term $\frac{\eta_s}{1-\eta_s}$ is a constant, the slope parameter on the log of the wage-to-vehicle price ratio, estimated by the OLS coefficient on $\log\left(\frac{w}{p_M}\right)$, is the sectoral elasticity of substitution between motor vehicles and labour, σ_s. Results of this regression for each agriculture and non-agriculture are shown in Table 3. As shown in Table 3, as expected, the estimated elasticity of substitution between motor vehicle and labour inputs was greater than 1 in agriculture but less than 1 in non-agriculture. In other words, it was easier to swap between motor vehicles and labour in agriculture than in non-agriculture.

Table 3: Estimation of sectoral motor vehicle-labour elasticities of substitution in main panel 2016

	(1) Agriculture	(2) Non-agriculture
Log wage-vehicle price ratio	1.144***	0.476***
	(0.300)	(0.135)
Observations	54	54
Adjusted R^2	0.180	0.161

Standard errors in parentheses
Standard errors clustered at country level
Sources: Author's analysis; OECD 2021; ILO 2020
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second, it can be shown from the market clearing equation $B_M L_M = M_A + M_N$ that the equilibrium share of labour in the motor vehicle sector in terms of the other sectoral labour shares is as follows:

$$\frac{L_M}{L} = B_M^{\sigma_A - 1} \left(\frac{\eta_A}{1-\eta_A}\right)^{\sigma_A} \frac{L_A}{L} + B_M^{\sigma_N - 1} \left(\frac{\eta_N}{1-\eta_N}\right)^{\sigma_N} \frac{L_N}{L} \tag{21}$$

Using Equation 21, I plugged in sectoral labour shares for each 1995 and 2016 using ILO (2020) data along with the values estimated using OLS in Table 3 for σ_A and σ_N, and finally solved for η_A and η_N.

This approach to calibrating the production parameters σ_s and η_s allowed me to pin them down using cross-country variation over 54 countries, rather than variation over time between 1995 and 2016. In the short run, when the technology of capital in the economy can be of a fixed nature, substitution between inputs could be restricted by the form of capital in stock. Rather than explicitly including capital in my model, any effect of capital on production is implicitly captured in my total factor productivity parameters. However, Stefanski (2014) argued that the alternative time series approach to calibrating these production parameters using a relatively short time period may pick up shorter-run responses to price changes before capital has had time to upgrade in the long run. Therefore, calibrating production parameters to cross-sectional data was more appropriate for measuring the long-run ease of substitution between labour and motor vehicles.

This left only two further parameters to be calibrated, the utility weight on the agriculture good ϕ and the subsistence level of the agriculture good $\overline{c_A}$. Starting from market clearing condition $Y_A = Lc_A$, substituting in agriculture production technology for Y_A and Equation 14 for c_A and then re-arranging, it can be shown that the share of total labour employed in the agriculture sector is given by:

$$\begin{aligned}\frac{L_A}{L} =& \frac{B_M^{\frac{\sigma_A}{\sigma_A-1}}}{B_A}(1-\eta_A)^{\sigma_A}(\eta_A^{\sigma_A}B_M^{\sigma_A}+(1-\eta_A)^{\sigma_A}B_M)^{\frac{-\sigma_A}{\sigma_A-1}}... \\ &...(\phi B_A B_M^{\frac{1}{1-\sigma_A}}(\eta_A^{\sigma_A}B_M^{\sigma_A}+(1-\eta_A)^{\sigma_A}B_M)+(1-\phi)\overline{c_A})^{\frac{1}{\sigma_A-1}}\end{aligned} \tag{22}$$

I filled in the agriculture labour share using ILO (2020) data and productivity values using UN (2021a) data for each 1995 and 2016, in addition to the σ_A and η_A parameters calibrated previously, and finally solved these two simultaneous equations for $\overline{c_A}$ and ϕ.

Table 4 displays the parameters selected by this calibration procedure. This shows that total factor productivity was growing in each sector between 1995 and 2016, but that this growth was almost 5 times higher in agriculture than in non-agriculture. The calibrated annualised growth rate in motor vehicle total factor productivity of 1.6 per cent as shown in Table 4 is close to an estimate of 1.09 per cent by Bogart (2014) for annual total factor productivity growth in overland passenger transport during industrialisation in Great Britain (between 1700 and 1870).[8] This suggests that my approach of drawing on total factor productivity growth in the wider transport sector rather than motor vehicles specifically is reasonable in the absence of more disaggregated data for my model of structural transformation. As expected, Table 4 confirms that the motor vehicle emissions factor was decreasing between 1995 and 2016 with improved fuel efficiency, with a calibrated annualised growth rate of -4.9 per cent.

Table 4 also shows that, as expected, the elasticity of substitution between motor vehicle and labour inputs was greater than 1 in agriculture but less than 1 in non-agriculture, while the motor vehicle share parameter was slightly higher in non-agriculture than in agriculture. It is also evident from Table 4 that the majority of the representative consumer's utility weight was placed on the composite non-agriculture

8. Meanwhile, Bogart (2014) estimated annual total factor productivity growth in overland freight transport to be 2.06 per cent during this period in Great Britain.

Table 4: Calibrated parameter values: main panel aggregates 1995-2016

Parameter	Parameter description	Value	Target
$L_0, B_{s,0}$	Labour force and productivity, 1995	1.000	Normalisation
g_L	Labour force growth	1.004	Labour force growth
g_A	Agriculture TFP growth	5.031	Productivity growth in A
g_N	Non-agriculture TFP growth	1.095	Productivity growth in N
g_M	Motor vehicle TFP growth	1.603	Productivity growth in M
ρ_0	Motor vehicle emissions factor, 1995	1.000	Normalisation
g_ρ	Motor vehicle emissions factor growth	-4.941	Emissions factor growth
σ_A	Agriculture elasticity of substitution	1.144	Vehicle inputs in A, 2016
σ_N	Non-agriculture elasticity of substitution	0.476	Vehicle inputs in N, 2016
η_A	Agriculture vehicle share parameter	0.003	Vehicle inputs in A, 2016
η_N	Non-agriculture vehicle share parameter	0.004	Labour share in M, 1995
$\overline{c_A}$	Subsistence level of agriculture good	0.272	Labour share in A, 1995
ϕ	Agriculture utility weight	0.159	Labour share in A, 2016

TFP denotes total factor productivity. Annualised growth rates reported as percentages.

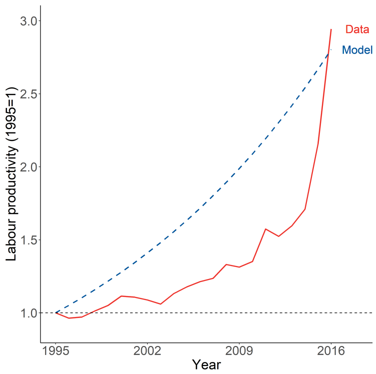
good.

5. Baseline simulation

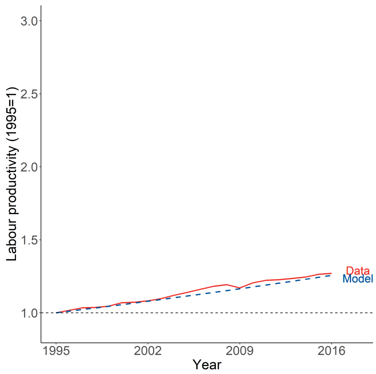
This section presents results from the baseline simulation of my calibrated model and compares these simulations to observed data. First, I simulated the model over the 1995-2016 period to which it was calibrated to determine its performance in reflecting real-world trends. Second, I extended the simulation period back to 1970 and compared this with observed trends as an assessment of the external validity of the model. Third, I utilised the model to simulate motor vehicle intensity among a cross section of my main panel. Finally, I used the model to examine three economies at different stages of the structural transformation process, France, South Korea and China, as case studies.

5.1. Calibrated period: 1995-2016

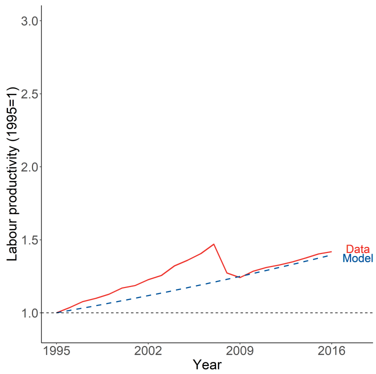
My model was calibrated to the 1995-2016 period, and the first model simulation task involved assessing the ability of the model to reflect various features of structural transformation and car intensity during this period. Figure 9 compares simulated data from the calibrated baseline model with data observed from 1995 to 2016. Despite the relative simplicity of the model, Figure 9 illustrates that the model was



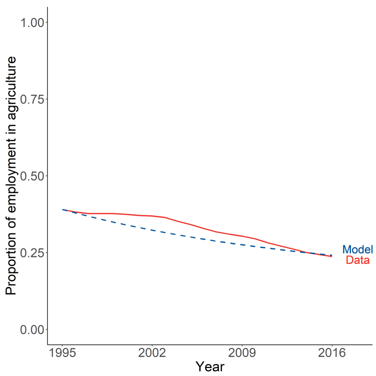
(a) Labour productivity, agriculture sector



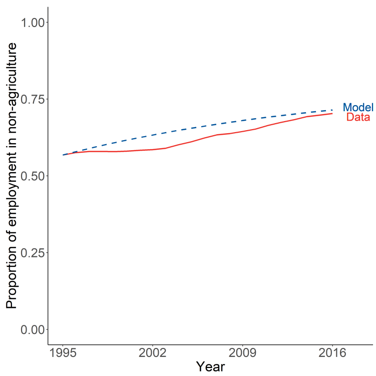
(b) Labour productivity, non-agriculture sector



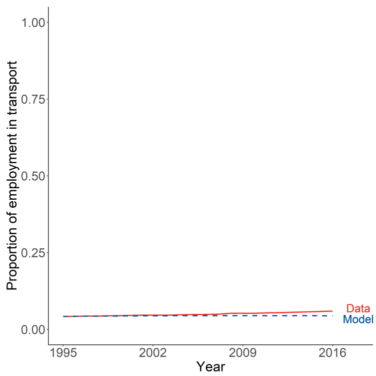
(c) Labour productivity, motor vehicle sector



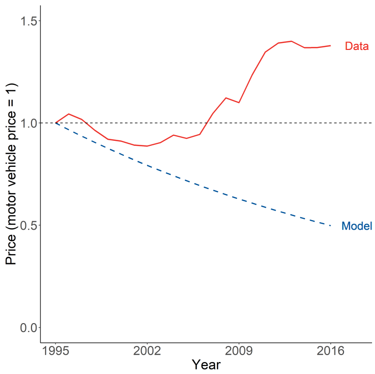
(d) Labour share, agriculture sector



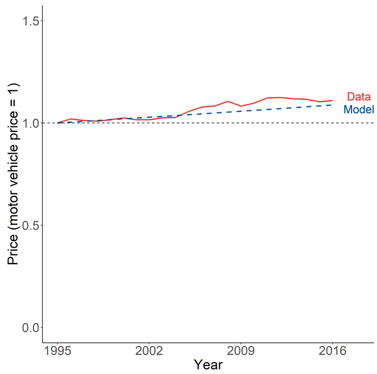
(e) Labour share, non-agriculture sector



(f) Labour share, motor vehicle sector



(g) Price, agriculture good (motor vehicle price=1)

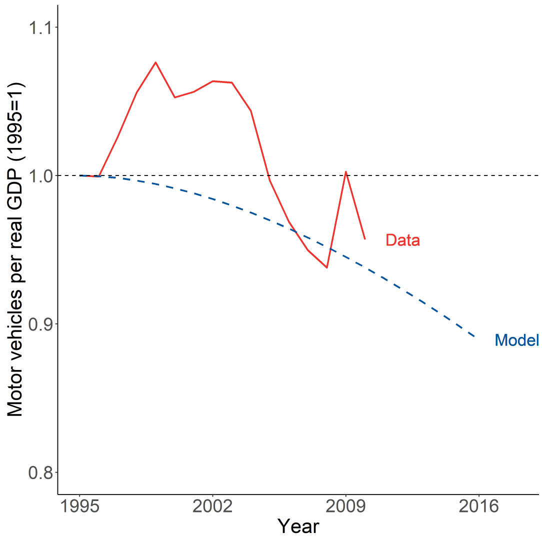


(h) Price, non-agriculture good (motor vehicle price=1)

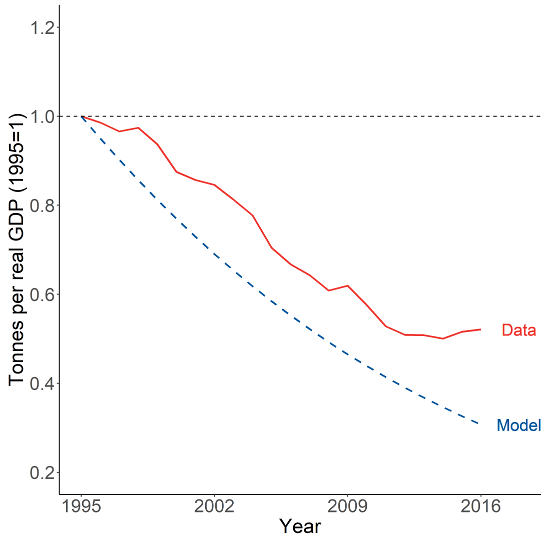
Figure 9: Structural transformation, baseline model simulation (blue dashed line) and data (red solid line), 1995-2016 calibration period.

constructed to capture the observed process of structural transformation very well in terms of labour shares and the price of the non-agriculture good relative to that of the motor vehicle good (this good took on the role of the numeraire in the model).

While the model reflected the initial decline in the relative price of the agriculture good during the early stages of the calibration period, it was unable to accurately reflect the later increase (see Figure



(a) Motor vehicle intensity in constant prices



(b) Carbon emissions intensity in constant prices

Figure 10: Intensity, baseline model simulation (blue dashed line) and data (red solid line), 1995-2016 calibration period.

9g). It may be that this observed increase was driven by factors outside the scope of my model, such as the Great Recession. A dip in labour productivity (measured here as GVA per worker) from 2007 into 2008, during the initial stages of the Great Recession, appears to have been particularly pronounced in the motor vehicle sector (measured here as the entire transport sector) in Figure 9c. As shown by the simulated data in Figure 9c, however, my model is not designed to capture such short-term shocks, but rather longer-term trends.

Figure 10 illustrates that the model implied a decrease in the levels of motor vehicle intensity and carbon emissions intensity over the 1995-2016 period. As these intensities would begin from 0 if the model was extended backwards to the start of the structural transformation process before increasing, the model is capturing the later decrease in intensity for the 1995-2016 period. The mechanism for the pattern in motor vehicle intensity is shown in Figure 11, which displays the current-price sectoral intensities that correspond to Equation 18 implied by the model over the calibration period. Motor vehicle intensity increased slightly in the agriculture sector, but decreased from a much higher base in the non-agriculture sector, producing the decrease in aggregate motor vehicle intensity over the calibration period. Given that the model calibration procedure set the elasticity of substitution parameters as $\sigma_A > 1$ and $\sigma_N < 1$, these sectoral intensity patterns imply that as expected, the vehicle-labour ratio was increasing in both sectors over the calibration period.

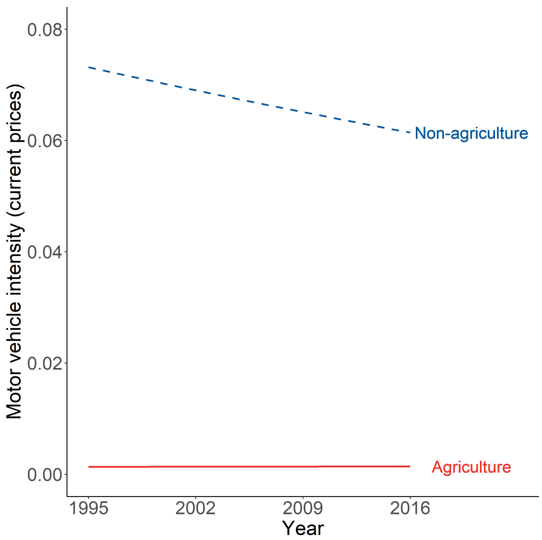


Figure 11: Sectoral motor vehicle intensity in current prices, baseline model simulation for agriculture (red solid line) and non-agriculture (blue dashed line), 1995-2016.

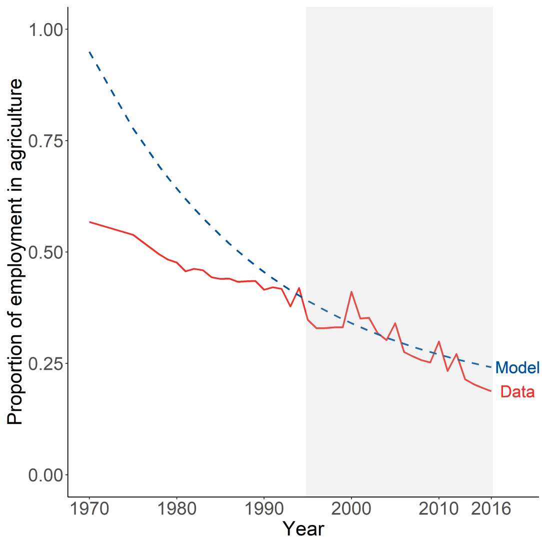
5.2. External validity: 1970-2016

How well was this model able to reflect structural transformation and intensity trends observed prior to the period to which the model is calibrated? Simulated data from the baseline model is compared with data observed from 1970 to 2016 in Figure 12, with the 1995-2016 calibration period shaded in grey. This exercise essentially tested the external validity of the calibrated model, and as shown in Figure 12, the model was able to capture key features of structural transformation observed prior to 1995. Interestingly, while the model could not capture the increase in the relative price of the agriculture good in the latter stages of the calibration period (see Figure 9g), it accurately predicted that this relative price had been mostly decreasing since 1970 (see Figure 12b).

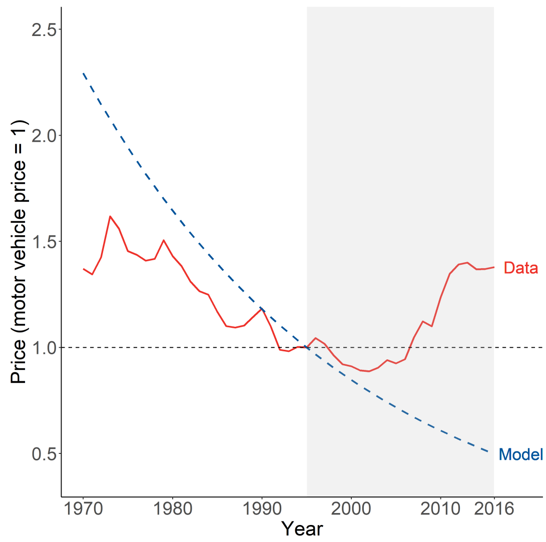
In addition, Figure 13 indicates that the model correctly implied that motor vehicle intensity had increased sharply prior to the calibration period, during which it peaked and began to decline. This represents clear evidence of the model's ability to produce a hump shape in motor vehicle intensity over the course of economic development. It is also a positive reflection of the external validity of my model that it was successful in capturing the broad trend in car intensity over a 25-year period prior to the period to which the model was calibrated.

5.3. Cross-sectional model fit

It is also worth determining whether this model of structural transformation can explain any of the variation in car intensity among a cross section of countries in a single year. I used my model to simulate levels of motor vehicle intensity among my main country panel in the year 2010. I calculated sectoral



(a) Labour share, agriculture sector



(b) Price, agriculture good (motor vehicle price=1)

Figure 12: Structural transformation, baseline model simulation (blue dashed line) and data (red solid line), 1970-2016. Grey shaded area shows model calibration period.

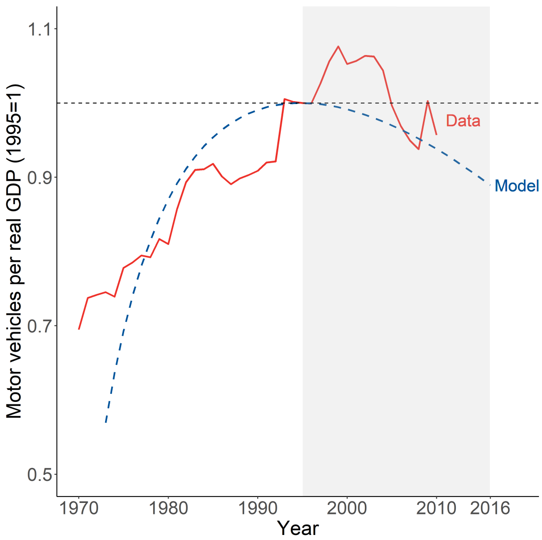


Figure 13: Motor vehicle intensity in constant prices, baseline model simulation (blue dashed line) and data (red solid line), 1970-2016. Grey shaded area shows model calibration period.

GVA per worker for each country relative to Great Britain using UN data (UN 2021a), and employed these values as sectoral total factor productivity parameters (B_A, B_N and B_M) for each country, leaving all other model parameters unchanged. Figure 14 plots modelled motor vehicle intensity values against observed car intensity values, while Table 5 shows results of a linear regression (column 1) and a log-log regression (column 2) of observed values on modelled values.

Table 5 shows that the linear model produced a lower value for Akaike's Information Criterion (AIC)

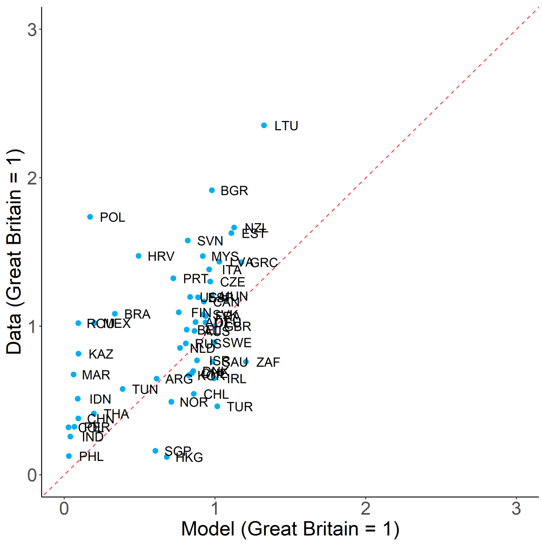


Figure 14: Simulated and observed motor vehicle intensity in constant prices, main panel 2010 (Great Britain = 1). Red dashed line shows 45-degree line.

Table 5: Cross-sectional model fit for main panel 2010

	(1) Observed intensity	(2) Log observed intensity
Modelled intensity	0.651***	
	(0.154)	
Log modelled intensity		0.324***
		(0.072)
Observations	54	54
Adjusted R^2	0.242	0.264
AIC	61	92

Standard errors in parentheses
AIC denotes Akaike's Information Criterion
Sources: Author's analysis; UN 2021a; Feenstra, Inklaar, and Timmer 2015; Palgrave Macmillan Ltd 2013b
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

than the log-log model, an indication that the linear regression was more appropriate for the data. Table 5 reports an adjusted R-squared value of 0.24 for the linear model (and 0.26 for the log-log model), indicating that in this 2010 cross section of 54 countries, the structural transformation model alone was able to account for approximately 24 per cent of observed variation in car intensity.

However, Figure 14 indicates that the model generally performs better among higher-intensity countries. A good model fit would be evident through points being consistently close to the 45-degree line. In Figure 14, while some higher-intensity countries such as Lithuania and Bulgaria deviate from the 45-degree line, more countries appear to deviate from the line at lower levels of intensity. This may partly be due to the aggregated data to which the model was calibrated, as this data is likely to be representative of the economies of some countries more than others. The mixed performance of the model may also stem to some extent from the configuration of the model itself. For example, my model does not include a government sector and thus abstracts away from taxes and subsidies. This would affect its performance in simulating intensity, particularly in economies with higher levels of taxes or subsidies.

5.4. Case studies: France, South Korea and China

I also used my baseline model to simulate motor vehicle intensity levels in France, South Korea and China over time. To achieve this, I recalibrated initial levels of productivity in the agriculture sector, $B_{A,0}$, in each of the three countries as a proportion of the productivity aggregated across my main panel in 1995, while leaving all other model parameters unchanged. These observed proportions were 1.4 for France, 0.41 for South Korea and 0.05 for China. For each country, I valued quantities in constant 2005 prices from the France model when calculating simulated intensity levels.

These countries represent three different stories of structural transformation, as shown in Figure 15. France and South Korea are both highly developed economies, but South Korea experienced its structural transformation away from agriculture much more recently, with the agriculture labour share still at 49 per cent in 1970 compared with just under 14 per cent in France. China, meanwhile, remains at an earlier stage of the structural transformation process, with just under 38 per cent of total employment still accounted for by the agriculture sector in 2010 (ILO 2020). Based on this, these three economies are interesting case studies to compare against each other in simulating motor vehicle intensity patterns over time.

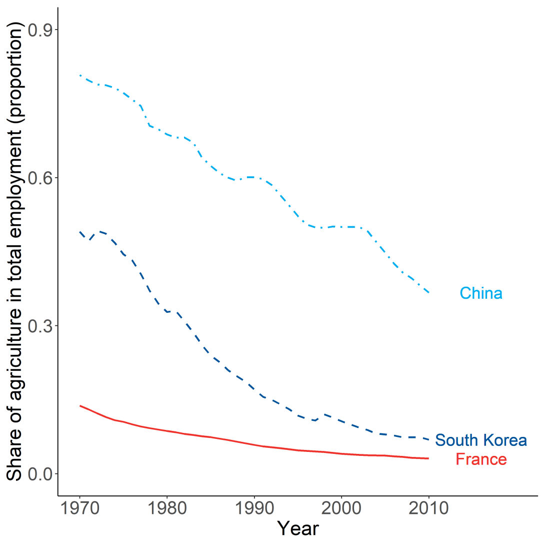


Figure 15: Agriculture employment shares, 1970-2010, France (red solid line), South Korea (blue dashed line) and China (light blue dot-dashed line). Source: Author's analysis; ILO 2020.

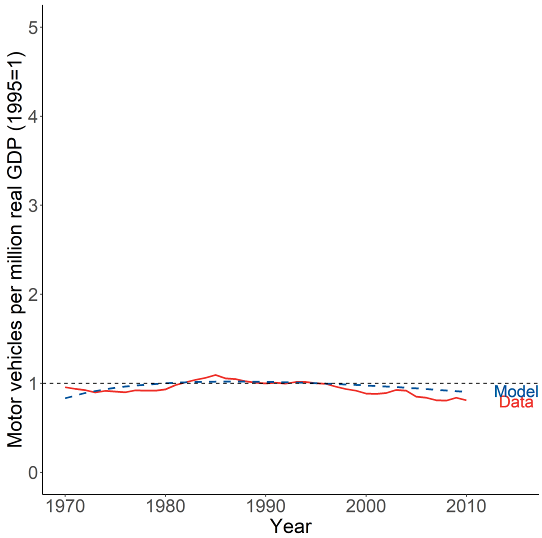
Figures 16a, 16b and 16c compare simulated levels of motor vehicle intensity with observed car intensity patterns for France, South Korea and China from 1970 to 2010. These show that the model performed well in capturing the broad changes in intensity in France and South Korea over the period. In Figure 16c, however, the model did not reflect the increase in intensity observed in China, as it implied that structural transformation would not begin until much later than in reality. This further suggests that my model as currently calibrated is more suited to demonstrating the structural transformation process of countries that have already largely completed the move away from agriculture or that are at an advanced stage of this shift, such as France or South Korea, than countries in an earlier phase of development, such as China.

As previously discussed, Figure 14 also indicates that the model performed better among countries with intensity levels similar to that of South Korea. A model calibrated to target data from a developing country, rather than data aggregated across a panel of mostly OECD members, may better capture observed patterns for a country such as China. For example, sectoral levels of growth in total factor productivity may differ for developing countries. Alternatively, the model itself could be further developed to include a government sector that incorporates taxes and subsidies. Another possible approach would be to introduce 'wedges' that capture the observed country- and year-specific deviations from the baseline model simulation. These wedges could be interpreted as distortions that arise due to differences between countries in terms of a myriad of factors such as taxation, institutions, climate, natural resources or geography, and would appear in the model in a similar fashion to a tax or productivity shock. Such an approach has been followed by Stefanski (2017), Duarte and Restuccia (2010) and Gollin, Parente, and Rogerson (2002), for example.

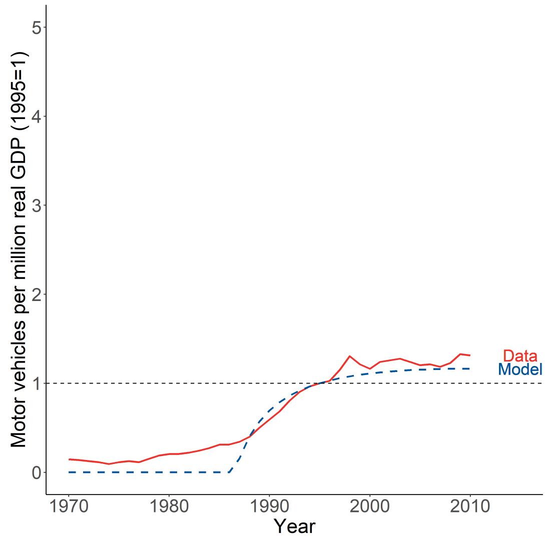
Having demonstrated the performance of my model in capturing observed intensity patterns, I then extended the simulation out to 2120 and compared the predicted intensity levels of the three countries. The results of this exercise are displayed in Figure 16d.

The model correctly implied that China would begin the process of structural transformation at a later stage than in South Korea, which in turn would begin this process later than France, although it clearly overestimated how long it would take before China began shifting to non-agriculture. As illustrated in Figure 16d, in terms of simulated motor vehicle intensity, the model suggested that South Korea would rapidly catch up with France during the early stages of transformation when the economy was shifting from agriculture to the much more intensive non-agriculture sector. Interestingly, however, it also suggested that intensity would peak at a marginally lower level in South Korea than in France. Relative to 2010, the model predicted that car intensity would be 35 per cent lower in France and 15 per cent lower in South Korea by 2040.

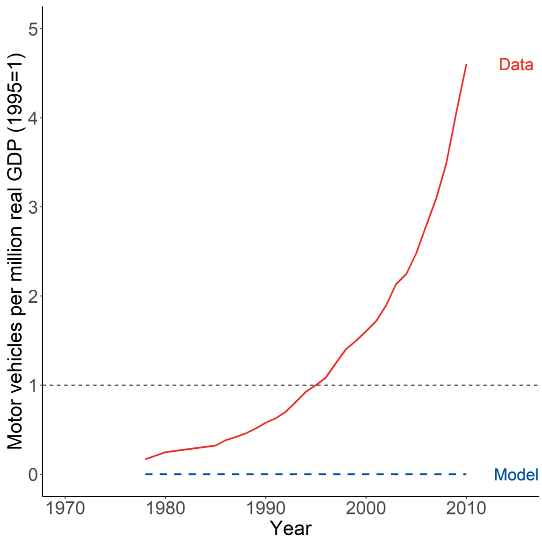
Meanwhile, the model implied that China would also eventually experience a high level of car intensity growth when transitioning from agriculture to non-agriculture, but that this too would level off and decrease. It also implied that this levelling off would occur at a lower level of intensity than in South



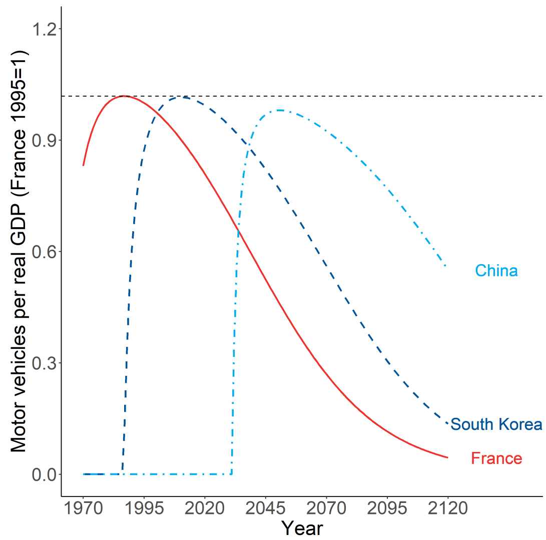
(a) Baseline simulation (blue dashed line) and data (red solid line), France 1970-2010.



(b) Baseline simulation (blue dashed line) and data (red solid line), South Korea 1970-2010.



(c) Baseline simulation (blue dashed line) and data (red solid line), China 1970-2010.



(d) Simulation of motor vehicle intensity, France (red solid line), South Korea (blue dashed line) and China (light blue dot-dashed line), 1970-2120. Horizontal dashed line shows peak intensity for France.

Figure 16: Baseline simulations of motor vehicle intensity for France, South Korea and China. Sources: Author's analysis; Palgrave Macmillan Ltd (2013b)

Korea. However, given the failure of the model to reflect earlier observed levels of car intensity in China, the future simulation for China should be treated with caution.

6. Role of structural transformation

Having established my model's ability to capture key observed trends in structural transformation and car intensity, I used the model to determine the role played by structural transformation in generating a hump-shaped pattern in intensity. This involved the simulation of two counterfactual models and comparing them to the baseline model. The first counterfactual model imposed that structural transformation did not happen at all, while in the second counterfactual, the process of structural transformation was delayed. For illustrative purposes, I extended these simulations backwards to 1970 and forwards to 2120 under the assumption that model parameters and growth rates in sectoral productivity remain at their calibrated 1995-2016 levels. When calculating simulated intensity levels in each model, I valued quantities in constant 2005 baseline model prices.

6.1. Counterfactual 1: No structural transformation

What is the role of structural transformation in generating this hump-shaped pattern in intensity? To answer this question, a counterfactual must be posed: what would happen in an economy where structural transformation did not occur? In my first counterfactual model, I reduced the multi-sector model to a one-sector model, producing a model economy where structural transformation between sectors was impossible. To achieve this, I essentially merged the agriculture and non-agriculture sectors into a single 'non-agriculture' sector. This involved re-calibrating the remaining model parameters after the removal of a separate agriculture sector, and details of this procedure are provided in Appendix C. As a result, in this experiment, no labour was ever allocated to a separate agriculture sector and, therefore, no structural transformation occurred.

The 'One-sector' scenario in Figure 17a shows the simulated evolution of motor vehicle intensity in this counterfactual model. Compared with the baseline model, intensity was initially higher in the one-sector model given the non-agriculture nature of the single final sector, and crucially, it decreased at a gradual but relatively uniform rate for the duration of the simulation rather than increasing sharply before levelling off and decreasing. This illustrates the key role of structural transformation in generating a hump-shaped pattern in intensity in my baseline model: a one-sector model was unable to echo the hump-shaped pattern in intensity that a two-sector model could.

The key mechanism for this difference in the two-sector model was the endogenous decline in the aggregate elasticity of substitution between motor vehicles and labour inputs. This aggregate elasticity was essentially an average of sectoral elasticities in agriculture and non-agriculture, weighted by the respective labour shares. As shown in Figure 17b, given a sectoral elasticity of greater than 1 in agriculture and less than 1 in non-agriculture in the two-sector baseline model, the aggregate elasticity was endogenously falling during structural transformation. In the one-sector model, however, without structural transformation this aggregate elasticity was constant (see Figure 17b).

This one-sector counterfactual simulation showed that in the absence of a structural transformation from one sector to another, the hump-shaped pattern did not emerge. Therefore, in my model economy, the transition between sectors that were characterised by different production processes was crucial in generating a hump-shaped trend in intensity. This represents further evidence in favour of the theory that structural transformation is a factor in producing a hump shape in car intensity.

It is also worth noting that the different intensity patterns between the baseline model and the 'One-sector' counterfactual had implications for simulated carbon emissions. Total carbon emissions over the 1970-2120 simulation period were 19 per cent higher in the one-sector counterfactual model than in the baseline model.

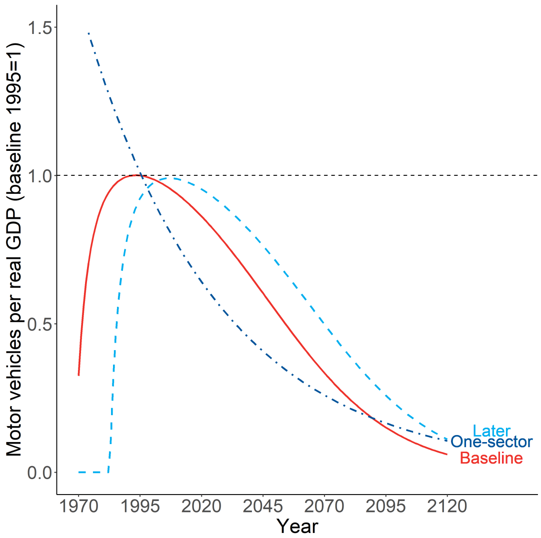
6.2. Counterfactual 2: Later structural transformation

How would aggregate motor vehicle intensity evolve if the structural transformation process occurred at a later stage? This question is particularly relevant for countries that remain dependent on an agriculture sector and that are still increasing in car intensity. In this second counterfactual exercise, I reduced the initial level of total factor productivity in the agriculture sector, $B_{A,0}$, from 1 to 0.6 and left all other model parameters, including the growth rate in agriculture total factor productivity g_A, unchanged. This experiment allowed me to explore the effect of a delayed structural transformation on motor vehicle intensity in my model economy.

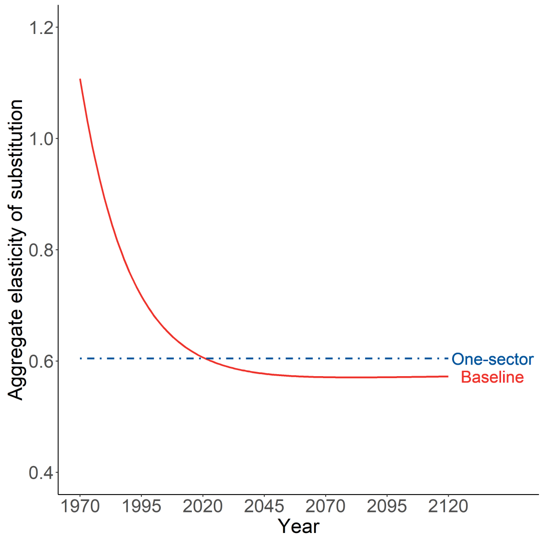
The simulated levels of motor vehicle intensity over time in this second counterfactual model are illustrated by the 'Later' scenario in Figure 17a. The model implied that intensity would still evolve in a hump-shaped manner as in the baseline model but with the initial increase starting later, but interestingly, that intensity would peak at a slightly lower level than in the baseline model.

This finding could be explained intuitively by the switch away from agriculture occurring at a later stage in the development of the non-agriculture sector, by which time it has decreased in intensity to a lower level than was the case during the transformation in the baseline simulation. This result suggests that countries that are still experiencing an increase in car intensity will ultimately reach a peak as they structurally transform, but that this plateau may be found at a lower altitude than that experienced by economies that industrialised earlier.

This counterfactual model also had interesting implications for carbon emissions. Relative to the baseline model, over the entire 1970-2120 simulation period, total carbon emissions were 37 per cent lower in the 'Later' counterfactual scenario. This lower level of pollution was due to a combination of intensity peaking at a slightly lower level and the increase in intensity occurring at a later stage when the fuel efficiency of vehicles had improved.



(a) Transport intensity in constant prices. Horizontal dashed line shows peak intensity for baseline.



(b) Aggregate elasticity of substitution between motor vehicle and labour inputs.

Figure 17: Simulations 1970-2120 using baseline model (red solid line), one-sector model (dark blue dot-dashed line), and later structural transformation model (light blue dashed line).

7. Empirical analysis

Having proposed a theoretical model and conducted counterfactual exercises to argue that structural transformation has played a role in generating observed hump-shaped patterns in car intensity, I conducted a semi-parametric regression analysis using observed data to empirically test this theory.

7.1. Method

To empirically test for a relationship between car intensity and structural transformation, I employed locally weighted scatter plot smoothing (LOWESS), which represents a non-parametric approach to examining a relationship between two variables. LOWESS, a modelling method proposed by Cleveland (1979) and further advanced by Cleveland and Devlin (1988), calculates a smoothed value y_i^s for each observed value y_i of a dependent variable by fitting simple regression models to local subsets of the data. Subsets of the data are determined by a nearest neighbour algorithm. Assuming the independent variable x_i is ordered across N total observations, such that $x_i \geq x_{i+1}$ for $i = 1, ..., N-1$, each smoothed value y_i^s is calculated using observations from $i_- = \max(1, i-k)$ to $i_+ = \max(i+k, N)$, where $k = \left\lfloor \dfrac{N \times bandwidth - 0.5}{2} \right\rfloor$. The 'bandwidth' of this algorithm is set by the researcher, with a greater bandwidth imposing a greater degree of smoothing. Within these local subsets, each included observation j is weighted according to a 'tricube' weight function with weights calculated as $w_j = \left\{1 - \left(\frac{|x_j - x_i|}{\Delta}\right)^3\right\}^3$, where $\Delta = 1.0001 \times \max(x_{i_+} - x_i, x_i - x_{i_-})$. Each value of y_i^s is thus a weighted least squares regression predication of y_i at x_i based on a local subset of data.

Crucially, the researcher imposes no global functional form to fit a model to the data. The localised nature of this modelling method, with models being fit only to segments of the data, means that it tends to follow the data rather than assumptions imposed by the researcher. In other words, LOWESS allows the data to do the talking.

Of course, there are other factors that may also affect car intensity. To account for these possible factors, I first ran a fixed effects regression of car intensity:

$$intensity_{i,t} = \alpha + \sum_{t=1971}^{2010} D_t + \sum_{i=1}^{M-1} G_i + X_{i,t} + \varepsilon_{i,t} \tag{23}$$

In Equation 23, the dependent variable $intensity_{i,t}$ was car intensity in country i and year t. Country and year fixed effects were both included as D_t and G_i respectively, with the number of countries in the panel given by M, to capture any factors that were specific to a particular country or year.

I also included a vector of four control variables, $X_{i,t}$, to capture factors suggested in the literature that may have been both country-specific and time-varying, as these would not have been accounted for by the fixed effects. First, I controlled for enrolment in tertiary education as higher enrolment may lead more younger people to delay car ownership (Delbosc and Currie 2013; Kuhnimhof et al. 2012). Second, I included the old-age dependency ratio to account for higher car ownership among older adults (Kuhnimhof, Zumkeller, and Chlond 2013). Third, I adjusted for road gasoline (petrol) prices to account for their influence on car intensity (Bastian, Börjesson, and Eliasson 2016; Bastian and Börjesson 2015; Grimal, Collet, and Madre 2013). I followed Bastian, Börjesson, and Eliasson (2016) in including the log of road gasoline prices in the regression model. Fourth, I included railway density as a proxy variable for the extent of public transport infrastructure on the basis that higher public transport availability may reduce car use (Newman, Kenworthy, and Glazebrook 2013).

In addition, I clustered standard errors at the country level. This allowed for potential correlations between the standard errors of observations from the same country, acknowledging possible factors such as country-specific measurement error when quantifying uncertainty.

Having run the fixed effects regression in Equation 23 and estimated residuals, I employed LOWESS to test for a relationship between these residuals and a measure of structural transformation that I calculated as 1 minus the agriculture labour share. This is based on the fact that countries with higher levels of GDP per capita have smaller shares of total employment devoted to agriculture, as previously shown in

Figure 8a. This essentially tested for a relationship between structural transformation and the remaining variation in car intensity that could not be explained by the fixed effects and control variables included in Equation 23. While Equation 23 imposed parametric assumptions on the relationships between car intensity and the fixed effects and other independent variables, deploying LOWESS laid down no such assumptions on the relationship with structural transformation. In implementing LOWESS, I specifically used running-line least-squares smoothing with the bandwidth set to 0.8, 0.6 and 0.4 to assess different levels of smoothing.

Finally, I ran four further regressions of car intensity based on my LOWESS results to empirically test the hypothesis that structural transformation was associated with car intensity. First, using the functional form suggested by the LOWESS results, I regressed car intensity on structural transformation without including fixed effects or any other independent variables. Second, I again regressed car intensity on structural transformation, this time including country fixed effects but not including year fixed effects. Third, I added year fixed effects to the car intensity regression. Finally, I then added structural transformation to the full fixed effects regression with controls shown in Equation 23, again using the functional form suggested by the LOWESS results. I conducted this empirical analysis using Stata/MP 16.1.

7.2. Data

I employed my main panel dataset for this empirical analysis, which included data on car intensity (Palgrave Macmillan Ltd 2013b) and the agriculture labour share (ILO 2020). I added data for my four control variables to this collated panel. The old-age dependency ratio, available from The World Bank (2019), measures the number of persons in the population older than 64 for every 100 persons aged between 15 and 64. Tertiary education enrolment, sourced from The World Bank (2022), is the ratio of total enrolment in tertiary education (regardless of age) to the population in the age group typically corresponding with tertiary education. For road gasoline prices, I used the country-level end-use real price index (2015=100) for unleaded motor gasoline in the IEA Energy Prices and Taxes database (IEA 2022a). I calculated railway density, in kilometres of open railway per square kilometre of land area, by combining data on railway length from Palgrave Macmillan Ltd (2013a) with land area data from The World Bank (2023). Further details on these variables, including definitions, data sources and descriptive statistics, are available in Appendix A.

Of course, there was a possibility that some of these independent variables may have been correlated with each other, raising the spectre of multicollinearity. A strong correlation, indicated by a correlation coefficient of approximately 0.7 or higher, between any of these variables would have been of particular concern. In Appendix A, however, I include a table of correlation coefficients showing that the highest correlation was only moderate at 0.56 (between the old-age dependency ratio and tertiary education enrolment).

7.3. Results

Column 1 of Table 6 displays results for the fixed effects regression described in Equation 23, while Figure 18 illustrates the country fixed effects estimated for this regression. The directions of the coefficients on the control variables in column 1 were generally as expected based on the literature. A higher old-age dependency ratio was associated with higher car intensity, consistent with the hypothesis that older people are more likely to own a car. While only significant at the 10 per cent level, log fuel prices were negatively associated with car intensity. The coefficients on the tertiary enrolment and railway density variables were not statistically significant. In terms of the country fixed effects, Figure 18 indicates that, for example, car intensity tended to be lower in countries such as South Korea and Norway, but higher in countries such as Poland and Bulgaria. This country-specific variation, along with year-specific factors that did not vary across countries and the control variables, was accounted for in estimating Equation 23, with the remaining variation in car intensity that could not be explained by these factors comprising the residual.

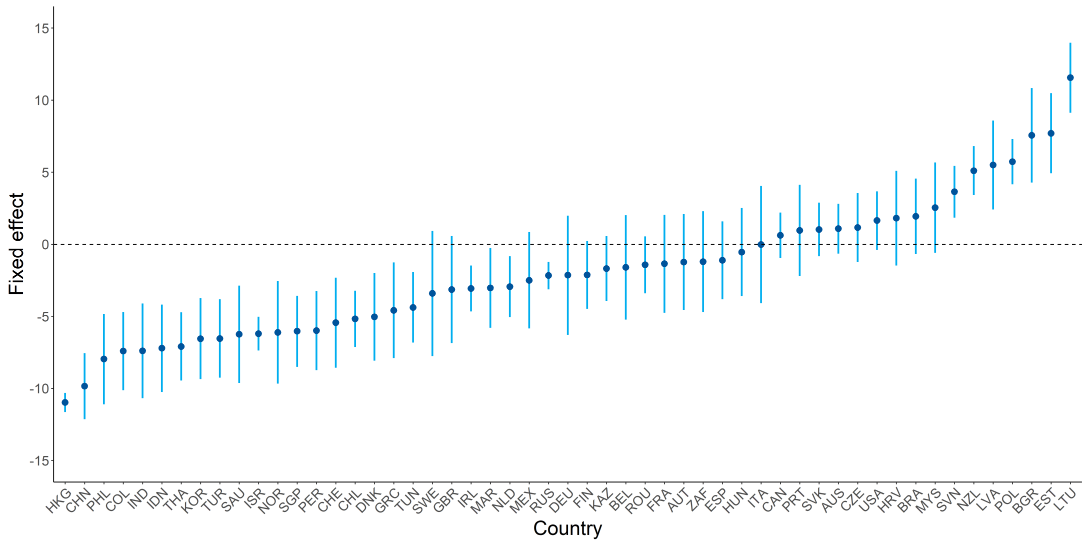


Figure 18: Estimated country fixed effects and 95 per cent confidence intervals from regression model of car intensity, main panel 1970-2010. Standard errors clustered at country level. Sources: Author's analysis; Palgrave Macmillan Ltd 2013b.

Using LOWESS, Figure 19 indicates a hump-shaped non-linear relationship between structural transformation and this residual estimated from the fixed effects regression in Equation 23. By applying LOWESS to this residual and structural transformation, I assessed the relationship between car intensity and structural transformation that was independent of country and year fixed effects, the dependency ratio, tertiary enrolment, fuel prices and railway density. Figure 19 is thus illustrating a hump-shaped relationship between car intensity and structural transformation, accounting for time-invariant country-specific factors, year-specific factors across countries, and the four additional control variables. Reassuringly, this relationship was consistent across varying levels of smoothing, with similar results produced whether the nearest neighbour algorithm's bandwidth was set to 0.8, 0.6 or 0.4. Given the semi-parametric nature of this approach, combining a parametric fixed effects regression with a non-parametric LOWESS method, Figure 19 represents clear empirical evidence of a hump-shaped relationship between car intensity and structural transformation.

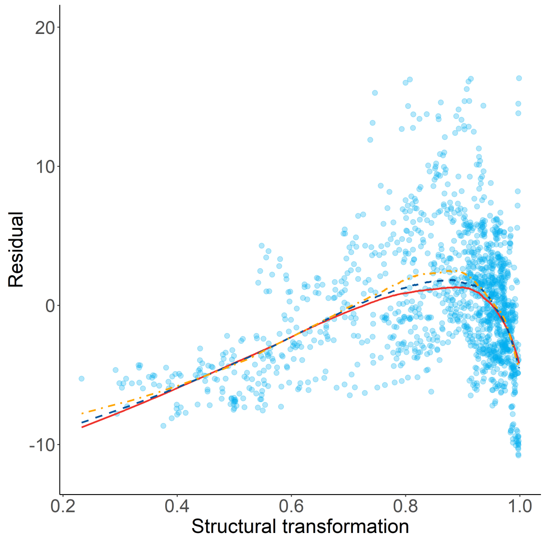


Figure 19: LOWESS, car intensity and structural transformation, main panel 1970-2010. LOWESS carried out using running-line least-squares smoothing. Points show country-year observations. Red solid line shows smoother with bandwidth = 0.8. Blue dashed line shows bandwidth = 0.6. Orange dot-dashed line shows bandwidth = 0.4. Sources: Author's analysis; ILO 2020; Palgrave Macmillan Ltd 2013b.

Given the hump-shaped relationship revealed in Figure 19, I then ran quadratic regressions of car intensity on structural transformation, first without including any fixed effects or other independent variables, to test the hypothesis that there was a non-linear relationship between these two variables. Column 2 in Table 6 confirms that car intensity was positively associated with structural transformation, but negatively associated with the square of structural transformation, indicating a hump-shaped relationship. This specification registered an adjusted R-squared of 0.24, indicating that 24 per cent of the variation in car intensity could be explained by structural transformation and its square alone. Interestingly, this echoed the 24 per cent of variation in observed car intensity that my structural transformation model was able to account for in a 2010 cross section (see Table 5). Columns 3 and 4 in Table 6 indicate that the quadratic association between car intensity and structural transformation held when accounting for country fixed effects and additionally for year fixed effects respectively.

Table 6: Regression model of car intensity across main panel 1970-2010

	(1)	(2)	(3)	(4)	(5)
Structural transformation		92.911***	25.678***	26.406***	32.752***
		(31.629)	(8.509)	(9.287)	(9.189)
Squared structural transformation		-53.247**	-14.253**	-13.800*	-18.295**
		(21.854)	(7.014)	(7.497)	(6.963)
Old-age dependency ratio	37.112**				39.762**
	(18.208)				(17.695)
Tertiary enrolment	-0.496				-0.778
	(1.682)				(1.388)
Log gasoline price	-2.199*				-2.060*
	(1.131)				(1.063)
Railway density	10.474				8.639
	(14.701)				(13.688)
Observations	1406	1406	1406	1406	1406
Adjusted R^2	0.095	0.239	0.042	0.075	0.150
Country fixed effects	Yes	No	Yes	Yes	Yes
Year fixed effects	Yes	No	No	Yes	Yes

Standard errors in parentheses
Standard errors clustered at country level
Within R-squared reported for fixed effects regressions (columns 1, 3, 4, 5)
Sources: Author's analysis; ILO 2020; The World Bank 2023, 2022, 2019; IEA 2022a; Palgrave Macmillan Ltd 2013b, 2013a
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Finally, column 5 in Table 6 presents results of the fixed effects regression in Equation 23 with structural transformation and its square added as independent variables based on the LOWESS results. The hump-shaped relationship between car intensity and structural transformation also persisted in this specification. Reassuringly, the associations with the dependency ratio and fuel prices remained consistent with the results shown in column 1.

As I measured structural transformation in this empirical analysis as 1 minus the proportion of total labour in the agriculture sector, the coefficient on the structural transformation variable of 32.8 in column 5 of Table 6 indicates that a 10 per cent increase in structural transformation (measured as a 10 per cent decrease in the agriculture labour share) was associated with an increase in car intensity of 3.28 cars per million USD of GDP. A 10 per cent increase in squared structural transformation was associated with 1.83 fewer cars per million GDP. Similarly, in column 5 the old-age dependency ratio was included in the regression model as a proportion, so a 10 per cent increase in this ratio was associated with 3.98 more cars per million GDP. Meanwhile, an increase in the log fuel price of 1 USD was associated with 2.06 fewer cars per million GDP in column 5, albeit only statistically significant at the 10 per cent level.

It should be noted that due to possible endogeneity, the results of this empirical analysis cannot be interpreted as casual effects. However, the results do provide further evidence of a hump-shaped relationship between car intensity and structural transformation that was independent of country and year fixed effects and the control variables.

8. Discussion

In a global context of global warming and climate change, establishing a clear understanding of factors behind peak car is important. In this study, I focused on the number of registered cars in the economy per unit of GDP, or car intensity, as an intrinsic component of car use that may be underlying the peak car phenomenon.

In a previous study, Kenworthy (2013) found car use per unit of GDP to have reduced among a sample of cities in developed countries. Building on this, I showed that car use per GDP evolves in a hump-shaped pattern over the full course of economic development, and that this dynamic stems mostly from car intensity. In other words, as GDP per capita increases, car intensity initially increases before reaching a peak and later decreasing. Car intensity reached a peak in Great Britain in 1992, for example, and has been gradually decreasing ever since. This phenomenon is relevant to the peak car debate regarding the apparent levelling off in annual per-capita distance travelled in cars and per capita car ownership among developed countries, as it offers insight into intrinsic factors that may be underlying peak car trends.

The central argument in this paper is that structural transformation, the reallocation of economic activity among the broad agriculture, manufacturing and services sectors, has a fundamental role to play in producing this relationship between car intensity and GDP per capita. A budding economy that is based on a labour-intensive agriculture sector may industrialise by veering towards a relatively more car-intensive non-agriculture sector as it grows, giving rise to an increase in car intensity. As the economy blossoms, however, the now dominant non-agriculture sector itself may become more capable of reducing its car intensity, leading the mature economy to experience a decrease in aggregate car intensity. This is a similar argument to that made by Stefanski (2014) in a study of structural transformation and oil prices.

I proposed a theoretical economic model characterised by a transition from a labour-intensive agriculture sector to a relatively more vehicle-intensive non-agriculture sector that was able to reflect the hump-shaped pattern in intensity. Structural transformation was generated by an income effect in this model, with non-homothetic preferences specified for the agriculture good. The calibrated model, with an endogenously decreasing aggregate elasticity of substitution between motor vehicle and labour inputs in production, was able to account for just under a quarter of observed variation in car intensity among a cross section of countries.

In addition, I conducted a counterfactual exercise using this model and an empirical semi-parametric regression analysis to demonstrate how structural transformation can generate a hump shape in intensity as the economy develops. While my baseline two-sector model characterised by structural transformation could reflect this pattern in intensity, a one-sector model could not account for it.

In a further counterfactual exercise, I found that economies that develop later reach a peak level of car intensity at a later stage, but that this peak occurs at a lower level than that experienced by countries that shifted away from agriculture earlier. This had important implications for carbon emissions, with total emissions over the entire simulation period 37 per cent lower in my counterfactual simulation than in my baseline model.

8.1. Policy implications

The findings of this paper have several implications for public policy. First, car intensity should continue to fall among developed countries. For example, my model predicted that car intensity will be 35 per cent and 15 per cent lower in France and South Korea respectively in 2040 than in 2010. A falling level of car intensity, with fewer cars required to produce economic output, suggests that developed countries have indeed reached peak car.

Second, as developing economies structurally transform, it can be expected that their levels of car intensity will increase. This increase is unlikely to be permanent, however, as intensity in these countries should eventually reach a peak before later decreasing. Due to the delayed increase in intensity, a lower peak level of intensity, and improvements in fuel efficiency of motor vehicles, it can also be expected that cumulative carbon emissions from cars during the process of structural transformation should be lower in these countries than in countries that industrialised earlier.

Third, how soon this peak is reached, and the subsequent rate of decrease, could potentially be influenced by targeting the productivity with which the non-agriculture sector deploys motor vehicle inputs, as a declining intensity in the non-agriculture sector is the channel through which aggregate intensity eventually falls in my model. Precisely how best to achieve this with levers available to public policy, such as taxation, is a potential avenue for future research.

8.2. Limitations and strengths

Certain limitations must be acknowledged in relation to this study. First, while the paper is focused on car intensity, the closest data available on sectoral inputs were categorised as 'manufacture of motor vehicle, trailers and semi-trailers' in the OECD Input-Output Tables (OECD 2021). Meanwhile, in the absence of more disaggregated data, I used 'transport' categories as proxies for the motor vehicle sector in GVA (UN 2021a) and employment (ILO 2020) data when calibrating my model. These categories are clearly broader and cannot be considered direct equivalents to private motor vehicles, and this is a limitation of the study due to data availability. Second, while my model allowed for separate rural agriculture and urban non-agriculture production, it had no formal spatial structure. One possibility for future research could be to further develop this structural transformation model into a spatial model where consumers endogenously choose where to live and work and whether to commute. Third, the calibrated model performed poorly in reproducing intensity patterns for developing economies such as China. In particular, the model overestimated the delay before structural transformation occurred. This could indicate that the data the model was calibrated to was more suited to developed economies. Fourth, while my regression analysis provided empirical evidence of a hump-shaped association between car intensity and structural transformation that was independent of country and year fixed effects and several control variables, these results could not be interpreted as causal due to possible endogeneity.

On the other hand, this paper can boast several key strengths. First, to my knowledge, this is the first study to empirically demonstrate a hump shape in car intensity. Second, despite the relative parsimony of my economic model, it was able to reflect this hump-shaped intensity pattern and performed well in reproducing intensity patterns among developed economies, indicating that structural transformation can explain some of the hump-shaped pattern in intensity. Third, the results of hypothesis tests using semi-parametric methods with observed data added further weight to the argument that structural transformation can play a role in generating this pattern. The paper, therefore, presents both theoretical and empirical arguments in favour of structural transformation influencing car intensity, and by extension, being an elementary factor that is underlying observed peak car trends. Based on these strengths, this paper represents a valuable contribution to peak car and structural transformation literature.

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Disclosure statement

The author has no competing interests to declare.

CRediT authorship contribution statement

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

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A. Data

A.1. Main country panel: 54 countries

Using a range of different sources, I constructed a panel dataset for 54 countries covering 22 years from 1995 to 2016 that could be employed to calibrate the structural transformation model. I also used this data to illustrate patterns in PKM intensity, and in conducting an empirical analysis of car intensity using regression models.

Based on data availability, the following 54 countries were included in my main country panel: Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, China (Hong Kong SAR), Colombia, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Israel, Italy, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Peru, Philippines, Poland, Portugal, Republic of Korea, Romania, Russian Federation, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkey, United Kingdom, United States. This includes 34 OECD members, 5 countries designated by the OECD as 'key partners', and 15 non-members. The agriculture labour shares and values of real GDP per capita of the 54 included countries in 2016 are illustrated in Figure 8a.

This section provides details on the various data sources collated in the panel. As shown in Table 7, I considered 'agriculture' to correspond to section A in the International Standard Industrial Classification of All Economic Activities (ISIC) Revision 4 (UN 2008) and 'non-agriculture' to correspond to the aggregation of sections B-G and I-U, with section H being considered 'transport' as a proxy for private motor vehicles where more disaggregated data was not available.

Employment

I relied on data from the International Labour Organization (ILO) for levels of employment by economic activity (ILO 2020). I aggregated the sectoral data up to three broad sectors: agriculture, non-agriculture and transport. I then calculated sectoral labour shares as proportions of total employment. Without more disaggregated data, I used the transport labour share to correspond with the motor vehicle sector in my model. When aggregated across the 54 countries in my collated main panel, the transport labour share was just over 4 per cent in 1995 and had increased to just under 6 per cent by 2016. As the primary labour dynamic in my model is a large-scale shift from agriculture to non-agriculture, I contend that using this transport labour share as a proxy for employment in my motor vehicle sector is a reasonable approach given data limitations.

Table 7: Mapping International Standard Industrial Classification of All Economic Activities (Revision 4) sections to broad sectors

Agriculture	Non-agriculture	Transport
A: Agriculture, forestry and fishing	B: Mining and quarrying	H: Transportation and storage
	C: Manufacturing	
	D: Electricity, gas, steam and air conditioning supply	
	E: Water supply; sewerage, waste management and remediation activities	
	F: Construction	
	G: Wholesale and retail trade; repair of motor vehicles and motorcycles	
	I: Accommodation and food service activities	
	J: Information and communication	
	K: Financial and insurance activities	
	L: Real estate activities	
	M: Professional, scientific and technical activities	
	N: Administrative and support service activities	
	O: Public administration and defence; compulsory social security	
	P: Education	
	Q: Human health and social work activities	
	R: Arts, entertainment and recreation	
	S: Other service activities	
	T: Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	
	U: Activities of extraterritorial organisations and bodies	

Sources: Author's analysis; UN 2008

Value added and prices

For sectoral gross value added (GVA) from 1995 to 2016, both in constant and current prices, I sourced data from the United Nations (UN) National Accounts Main Aggregates Database (UN 2021a). This database provided sectoral GVA in constant 2015 US dollars (USD), and I re-based this to 2005 prices. I aggregated the GVA data up to the broad agriculture, non-agriculture and transport sectors, and again used the transport sector data for my model's motor vehicle sector.

Price indices for the agriculture, non-agriculture and transport sectors could then be calculated as the ratio of sectoral GVA in current prices to sectoral GVA in constant prices:

$$\frac{p_{s,t}}{p_{s,2005}} = \frac{GVA_{s,t}}{GVA_{s,2005}}, \quad s = A, N, T \tag{24}$$

The resulting indices were relative to the base year of the constant price GVA data, 2005 in the case of my collated dataset.

When comparing sectoral productivity across countries, however, it is important to account for any sectoral price differences between countries. For example, the relative price of the agriculture good may be different in Germany compared to India. Simply converting GVA data from local currencies to USD using market exchange rates ignores these differences in relative prices between economies.

To account for this, I calculated sectoral price levels using data from the International Comparison Programme (ICP), a database that provides values of final expenditure by category in 2005 (The World Bank 2005). This data is available as 'nominal' expenditure in current USD, converted from local currencies using market exchange rates, as well as 'real' expenditure in purchasing power parity (PPP) USD (The World Bank 2008), which allowed me to extract the relative price levels of sectors relative to the corresponding sector in the US in 2005. Specifically, I calculated the relative price level of sector s in country i as follows:

$$\frac{p_s^i}{p_s^{PPP}} = \frac{E_s^i}{E_s^{PPP}} \tag{25}$$

In Equation 25, E_s^i and E_s^{PPP} denote expenditure in country i and sector s in current USD and in PPP USD respectively.

The publicly available ICP data (The World Bank 2005) is disaggregated across several expenditure categories that can be mapped to the broad agriculture, non-agriculture and transport sectors in my model. Table 8 displays how I mapped ICP categories to these sectors. I aggregated expenditure across all corresponding categories for each broad sector before extracting relative price levels.

Having extracted the 2005 relative price levels of sectors across countries as in Equation 25, I converted the sectoral GVA data in constant 2005 USD (having re-based this data from 2015 prices) to 2005 PPP USD by dividing it by the corresponding relative price level.

Finally, I also used these 2005 relative price levels to adjust the 1995-2016 sectoral price indices that I calculated using UN (2021a) data. Specifically, I multiplied the price indices from Equation 24 by the relative price levels in 2005 from Equation 25 to get 1995-2016 indices of prices levels by sector across countries.

Sectoral motor vehicle inputs

I sourced data on sector-specific motor vehicle inputs from the OECD Input-Output Tables 2021 (OECD 2021), which provided annual inputs in current USD from 1995 disaggregated across 2-digit ISIC (Rev. 4) divisions. Using these categorisations, I assumed motor vehicle inputs to include inputs to each the broad agriculture and non-agriculture categories specifically from division 29 ('manufacture of motor

Table 8: Mapping International Comparison Programme 2005 categories to broad sectors

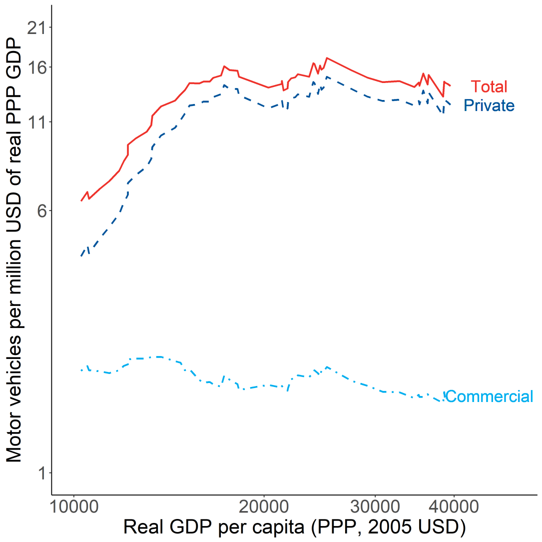
Agriculture	Non-agriculture	Transport	Not mapped
110100: Food and non-alcoholic beverages	110300: Clothing and footwear	110700: Transport	111300: Balance of expenditures of residents abroad and expenditures of non-residents in the economic territory
110200: Alcoholic beverages, tobacco and narcotics	110400: Housing, water, electricity, gas, and other fuels*		130000: Individual consumption expenditure by government
	110500: Furnishing, household equipment and routine maintenance of the house		140000: Collective consumption expenditure by government
	110600: Health - HHC*		170000: Balance of exports and imports
	110800: Communication		160100: Changes in inventories
	111100: Restaurants and hotels		160200: Acquisitions less disposals of valuables
	150100: Machinery and equipment		
	150200: Construction		
	150300: Other products		

* Expenditure data in USD not available in 2005.
Sources: Author's analysis; The World Bank 2005

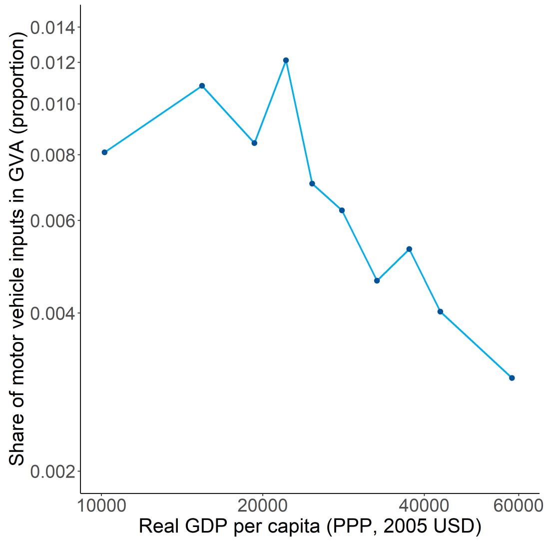
vehicle, trailers and semi-trailers'). I converted these inputs into shares of total value added (also from the Input-Output Tables in current USD) for each agriculture and non-agriculture, and multiplied these shares by sectoral GVA in 2005 PPP USD using the value added data to convert the input values into constant price values.

Of course, more disaggregated data would be more useful in the context of this study, as inputs from division 29 incorporate the manufacture of commercial motor vehicles and trailers in addition to private cars. However, using data from Mitchell's *International Historical Statistics* (Palgrave Macmillan Ltd 2013b) and from the Penn World Tables (Feenstra, Inklaar, and Timmer 2015), in Figure 20a I decomposed total motor vehicle intensity in Great Britain over the 1950-2010 period into private car intensity and commercial vehicle intensity. First, this illustrates that private car intensity in Great Britain since 1950 has been consistently and substantially higher than commercial vehicle intensity. Second, it indicates that there has been relatively little change in the level of commercial vehicle intensity since 1950 in Great Britain compared with the change evident in private car intensity. Third, it demonstrates that, given these two facts, a hump-shaped pattern can also be found when plotting the combined intensity of all motor vehicles against GDP per capita.

I also confirmed in Figure 20b that the hump-shaped pattern in intensity can be found using aggregate motor vehicle inputs per GDP, calculated using Input-Output data (OECD 2021), even though this data was only available from 1995 rather than from 1950. Based on this, while it is a data limitation of this study, I contend that it was reasonable to use this Input-Output data to calculate a proxy measure of sectoral car intensity in the absence of more disaggregated data.



(a) Motor vehicles per GDP and real GDP per capita, Great Britain 1950-2010. Axes transformed to $\log_e$ scales. Sources: Author's analysis; Feenstra, Inklaar, and Timmer 2015; Palgrave Macmillan Ltd 2013b.



(b) Aggregate motor vehicle inputs per GDP and real GDP per capita, main panel 1995-2016. X-axis transformed to $\log_e$ scale. Points show decile averages. Sources: Author's analysis; OECD 2021; Feenstra, Inklaar, and Timmer 2015.

Figure 20: Using OECD Input-Output Table data on motor vehicle inputs to calculate a proxy measure of sectoral car intensity.

Wage

In calibrating my model of structural transformation, I considered the economy wage (common across sectors) to be total GVA per worker in 2005 PPP USD. This was calculated using the collated employment and value added data.

Passenger kilometres by transport mode

For 29 of the 54 countries in my main panel, annual data on passenger kilometres (PKM) for road passenger vehicles (including private and commercial vehicles), rail and bus from 1970 to 2019 were also available from the International Transport Forum's Transport Statistics database (OECD 2017). The 29 countries were: Argentina, Australia, Austria, Belgium, Bulgaria, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Republic of Korea, Lithuania, Netherlands, Norway, New Zealand, Poland, Portugal, Russian Federation, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States. Given the data source, this 29-country subset mainly consisted of

OECD members, with Argentina, Bulgaria and Russia also included.

While I used my main panel covering 54 countries over the 1995-2016 period for calibrating my model, I used this 29-country subset from 1970 to 2019 to illustrate the observed hump-shaped pattern in PKM intensity. To calculate PKM intensity over time, I divided PKM by real GDP in constant 2005 PPP USD.

Old-age dependency ratio

For the empirical analysis involving regression models, I also sourced data from 1970 to 2010 on the old-age dependency ratio from The World Bank (2019). The old-age dependency ratio is defined as the number of persons in the population older than 64 for every 100 persons aged between 15 and 64. This ratio is available as a percentage, and I converted this to a proportion for the purposes on my empirical analysis.

Tertiary education enrolment

As a measure of enrolment in higher and further education, I employed the gross enrolment ratio in tertiary education, available from The World Bank (2022). This variable is defined as the ratio of total enrolment in tertiary education, regardless of age, to the population in the age group that would typically correspond with tertiary education. It is designed as a measure of the capacity of a country's tertiary education system (The World Bank 2022). The ratio is available as a percentage, and I converted this to a proportion for the empirical analysis.

Road gasoline price

I sourced data on road fuel prices from the International Energy Agency's (IEA) Energy Prices and Taxes database (IEA 2022a). Specifically, I employed the country-level household sector end-use real price index (2015 = 100) for unleaded motor gasoline (petrol). This index was calculated from a representative price of a combination of the most-consumed unleaded motor gasoline products (or leaded motor gasoline for earlier periods), with the nominal price index deflated using national Consumer Price Indices (IEA 2022b).

Railway density

Mitchell's *International Historical Statistics* included historical data on the length of railway open by country in kilometres. Data was available from 1970 to 2010 for my main panel, although this time range varied by country. I combined this data with data on land area from The World Bank (2023), which measured the total area of a country, excluding inland water bodies and national claims to coastal waters, in square kilometres. I divided railway length by land area to derive the density of railways in kilometres of railway per square kilometre of land.

A.2. Extended country panel: 88 countries

My 54-country panel also included annual data on GDP, the number of registered motor vehicles, and carbon emissions, which were available for a wider and more diverse panel of 88 countries. I used this extended 88-country panel for identifying patterns in car intensity. This panel included all countries from my main panel, in addition to the following: Albania, Algeria, Azerbaijan, Bahrain, Belarus, Bolivia (Plurinational State of), Bosnia and Herzegovina, Botswana, Congo, Costa Rica, Dominican Republic, Ecuador, Egypt, El Salvador, Eswatini, Georgia, Iran (Islamic Republic of), Iraq, Jamaica, Jordan, Kuwait, Lebanon, Mauritius, North Macedonia, Panama, Paraguay, Republic of Moldova, Serbia, Syrian Arab Republic, Taiwan, Trinidad and Tobago, Ukraine, Uruguay, Venezuela (Bolivarian Republic of). Car intensity levels and values of real GDP per capita for 2010 of the 88 countries included in my extended panel are illustrated in Figure 3b.

GDP

For a time series on GDP, I used real output-side GDP at chained PPPs in 2017 USD, sourced from the Penn World Tables (Feenstra, Inklaar, and Timmer 2015). For consistency with the rest of my collated data, I re-based this real GDP data to 2005 PPP USD.

Registered motor vehicles

I drew on Mitchell's *International Historical Statistics* for a time series on the number of private cars (Palgrave Macmillan Ltd 2013b). Data was available from 1950 to 2010, although this time range varied by country. This data included time series on 'private cars' and 'commercial vehicles', allowing the total number of motor vehicles to be calculated. However, the data was more widely available for private cars, so I used this in calculating car intensity. To calculate car intensity over time in the economy, I simply divided the number of private cars by real GDP in constant 2005 million PPP USD.

Figure 3a in the paper demonstrates the hump-shaped relationship between car intensity and GDP per capita in this extended panel by plotting decile averages, while Figure 2 depicts this hump shape for the UK. To confirm this relationship also holds across multiple countries, Figure 21 graphs individual line plots of the relationship between car intensity and GDP per capita for selected countries, providing additional evidence of a hump-shaped relationship.

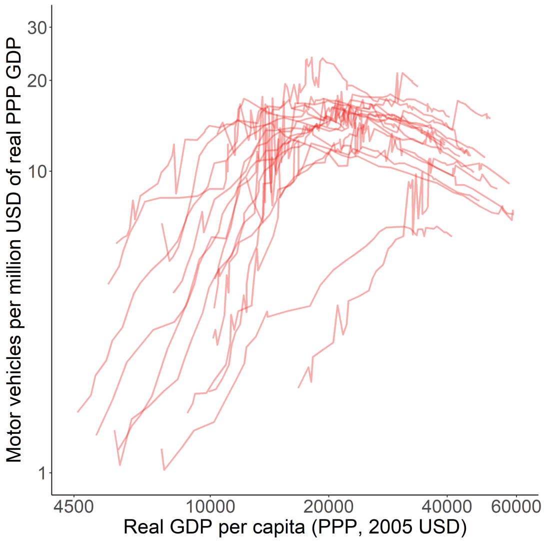


Figure 21: Private car intensity and real GDP per capita, selected countries from extended panel 1950-2010. Axes transformed to $\log_e$ scales. Sources: Author's analysis; Palgrave Macmillan Ltd 2013b; Feenstra, Inklaar, and Timmer 2015.

Carbon emissions

I obtained detailed estimates of greenhouse gas emissions among my extended panel for the 1971-2019 period from the IEA (2022c). Using this data, I added country-specific time series on total carbon dioxide emissions from fuel combustion, and also more specifically on emissions from the combustion of motor gasoline excluding biofuels for road transport, to my extended panel. The IEA estimated these emissions in kilo-tonnes of carbon dioxide using IEA energy databases and emissions factors. To calculate carbon emissions intensity for total fuel combustion and for road motor gasoline combustion, I divided these estimates by real GDP in constant 2005 million PPP USD.

A.3. Great Britain

I also collated data for a single developed economy, namely Great Britain (incorporating England, Scotland and Wales). I used this data to illustrate patterns in VKM and car intensity.

Vehicle kilometres by car

I sourced data on vehicle kilometres (VKM) by vehicle type, including a category for 'cars and taxis', from 1950 to 2019 from the UK Department for Transport (2021a). The UK Department for Transport (2021a) calculate annual traffic estimates for the UK using a combination of manual traffic counts, automatic traffic counters and data on road lengths. I combined this data on VKM by cars and taxis with Penn World Table data on real GDP (Feenstra, Inklaar, and Timmer 2015) to calculate VKM intensity by car.

Number of licensed cars

Data on the number of licensed vehicles by tax class, including a category for 'private cars', from 1950 to 2019 was also available from the UK Department for Transport (2021b). To calculate car intensity, I combined this data with Penn World Table data on real GDP (Feenstra, Inklaar, and Timmer 2015).

A.4. Empirical analysis

Table 9 presents descriptive statistics for the variables included in my empirical hypothesis tests. Country-year pairs missing observed data for car intensity (the outcome variable in this empirical analysis) were dropped, leaving 1,406 observations across the 54 countries of my main panel. For the remaining observations missing data for tertiary education enrolment, gasoline price or railway density, I reset values to 0 to preserve the observation. I generated a dummy variable corresponding to each of these three variables that was equal to 1 if its value had been missing and reset to 0, and included these dummy variables in any regression specifications that involved these variables. As shown in Table 9, missing data was a particular issue for my gasoline price variable, with data available for only 790 of 1,406 observations.

Table 9: Descriptive statistics of selected variables for main panel 1970-2010

	N	Mean	S.D.	Min.	Max.
Car intensity (cars/million USD)	1,406	11.06	5.77	0.16	29.82
Structural transformation (proportion)	1,406	0.86	0.16	0.23	1.00
Old-age dependency ratio (proportion)	1,406	0.17	0.07	0.05	0.31
Tertiary enrolment (proportion)	1,172	0.38	0.22	0.01	1.04
Regular unleaded gasoline price (2015=100)	790	93.64	20.18	53.15	174.06
Railway density (km of rail per sq. km)	1,223	0.04	0.03	0.00	0.15

N denotes observations. S.D. denotes standard deviation
Sources: Author's analysis; ILO 2020; The World Bank 2022, 2019; IEA 2022a; The World Bank 2023; Palgrave Macmillan Ltd 2013b, 2013a

Correlation coefficients between structural transformation (calculated as 1 minus the agriculture labour share), the old-age dependency ratio, tertiary education enrolment, the road gasoline price index and railway density are displayed in Table 10. This shows the highest correlation between variables to be moderate at 0.56, specifically between the dependency ratio and tertiary education enrolment.

Table 10: Correlation coefficients of selected variables for main panel 1970-2010

	Transformation	Dependency ratio	Tertiary	Gasoline price
Transformation	1			
Dependency ratio	0.539	1		
Tertiary	0.506	0.562	1	
Gasoline price	-0.143	-0.0556	-0.0840	1

Variable names abbreviated for illustrative purposes
Sources: Author's analysis; ILO 2020; The World Bank 2023, 2022, 2019; IEA 2022a; Palgrave Macmillan Ltd 2013a

B. Disaggregating non-agriculture

The 'non-agriculture' sector in my model consists of two principal components, industry and services. I considered 'industry' to correspond to the aggregation of sections B-E, and 'services' to correspond to the aggregation of section G and sections I-U, in the ISIC Revision 4 (UN 2008), with section H still kept aside as my motor vehicles sector. Figure 22 illustrates how observed car intensity evolves as the economies transition from agriculture to industry, and later to services. This provides some evidence that the initial increase in car intensity stems from a shift away from agriculture, but that the later decrease may only set in once the services sector assumes a greater role in the economy.

In Section 2 of the paper, I ran the following linear regression separately for the agriculture sector and for the 'non-agriculture' sector:

$$VehInputs_{i,t} = \alpha + \beta AgriLabour_{i,t} + \varepsilon_{i,t} \tag{26}$$

The dependent variable $VehInputs_{i,t}$ measures the share of sectoral value added (with value added measured in constant 2005 PPP USD) in country i in year t that is accounted for by motor vehicle inputs. The independent variable $AgriLabour_{i,t}$ represents the share of total employment in agriculture in country i and year t. This regression essentially relates sectoral motor vehicle intensity to the extent of structural transformation in each country over time, with the coefficient of interest β capturing the linear relationship between sectoral vehicle intensity and structural transformation.

Table 11 re-produces the results of this regression for agriculture (column 1) and non-agriculture (column 2) shown in the paper. But what if I disaggregated non-agriculture into its two components, industry and services? Columns 3 and 4 in Table 11 provide regression results for industry and services, showing that the non-agriculture sector appears to more closely resemble the services sector.

Since the agriculture labour share decreases during the process of structural transformation, Figures 23a and 23b depict regression lines for each of these specifications with the x-axis reversed and extended over the full domain of the agriculture labour share to illustrate progress in structural transformation.

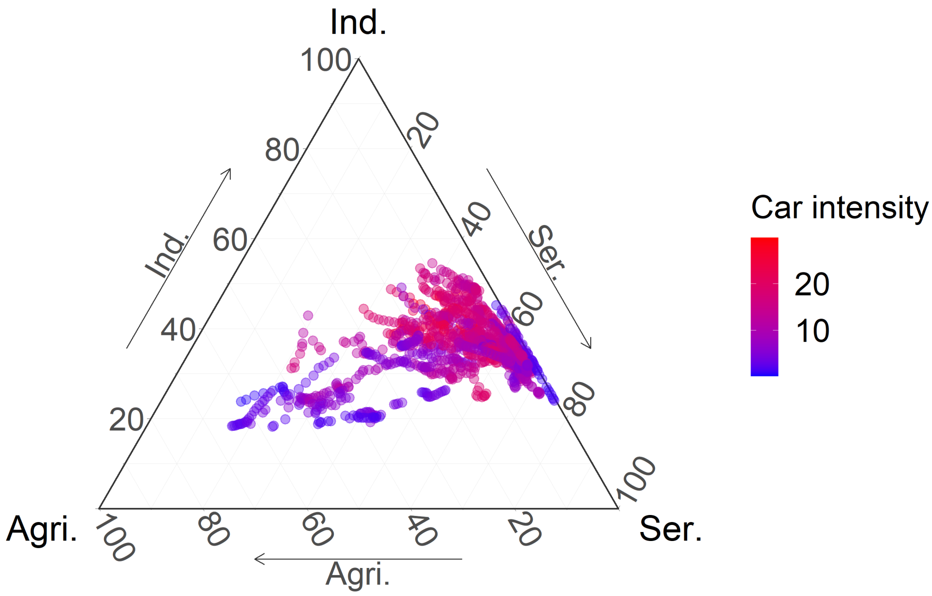


Figure 22: Ternary plot of sectoral labour shares and aggregate car intensity, main panel 1970-2019. Triangle sides show percentages of total employment in agriculture (agri.), industry (ind.) and services (ser.) sectors. Points, representing country-year pairs, are coloured by aggregate car intensity in private motor vehicles per million USD of real PPP GDP. Sources: Author's analysis; ILO 2020; Feenstra, Inklaar, and Timmer 2015; Palgrave Macmillan Ltd 2013b.

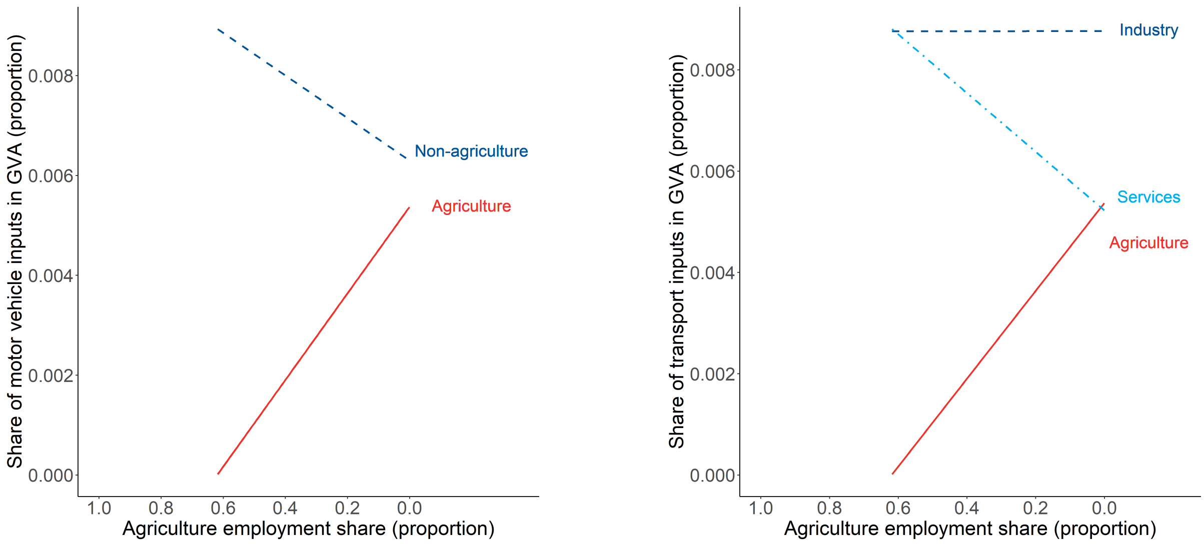
Table 11: Changes in sectoral motor vehicle inputs over process of structural transformation for main panel 1995-2016

	(1) Agriculture	(2) Non-agriculture	(3) Industry	(4) Services
Agriculture labour share	-0.009***	0.004***	-0.000	0.006***
	(0.001)	(0.001)	(0.002)	(0.001)
Observations	1188	1188	1188	1188
Adjusted R^2	0.031	0.009	-0.001	0.018

Standard errors in parentheses
Sources: Author's analysis; OECD 2021; ILO 2020; Feenstra, Inklaar, and Timmer 2015
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 23a simply re-produces the 2-sector regression lines shown in the paper, while Figure 23b presents regression lines for the 3-sector version.

Table 11 reveals a negative but statistically insignificant coefficient on the agriculture labour share



(a) Agriculture and non-agriculture.

(b) Agriculture, industry and services.

Figure 23: Changes in sectoral motor vehicle intensity over structural transformation as regression lines, main panel 1995-2016. X-axis extended over full domain and reversed for illustration. Sources: Author's analysis; OECD 2021; ILO 2020; Feenstra, Inklaar, and Timmer 2015.

variable in the industry sector's regression, indicating that a higher share of total employment in agriculture was associated with a lower share of motor vehicle transport inputs in the value added of the agriculture sector. Meanwhile, a positive coefficient was found on the agriculture labour share variable in the services regression. As illustrated in Figure 23b, this suggests that over the course of structural transformation, less motor vehicle transport was needed to produce one unit of output in services.

These additional results may shed some light on why motor vehicle intensity appears to decrease in non-agriculture during structural transformation. Rather than the industry sector becoming more efficient in its use of motor vehicles, these results suggest that the decrease actually stems from non-agriculture shifting from industry to services, which itself is initially more intensive but is becoming more efficient in its use of motor vehicles. This is in contrast a similar analysis of oil intensity by Stefanski (2014), who found oil intensity to be decreasing in both industry and services while increasing in agriculture among a sample of OECD countries between 1970 and 2000.

C. Model theory

I have assumed that my model economy operates in perfect competition. Figure 24 provides a stylised illustration of how agents interact in the market of this economy.

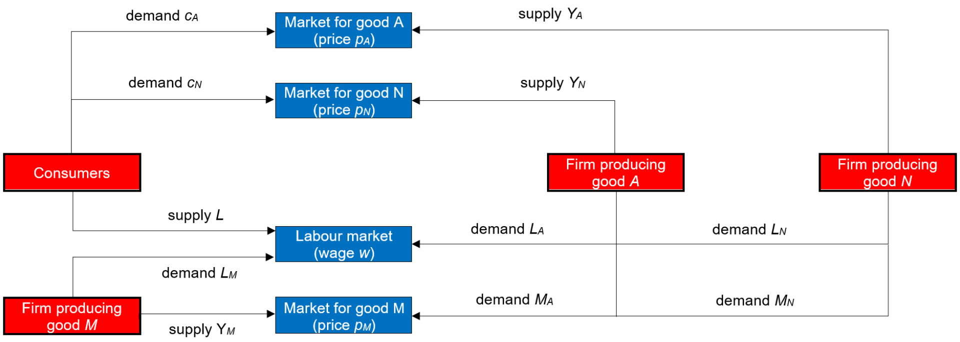


Figure 24: Market system in my economic model.

C.1. Consumers

I assume the consumer optimisation problem takes the form of a log utility function:

$$\begin{aligned} \max_{c_A, c_N} \quad & \phi \log(c_A - \overline{c_A}) + (1-\phi)\log(c_N) \\ \text{s.t.} \quad & p_A c_A + p_N c_N = w \end{aligned} \tag{27}$$

In this constrained maximisation problem, $\phi \in (0,1)$ represents the utility weight on the agriculture good. A subsistence level of the agriculture good is given by $\overline{c_A} > 0$. Figure 25 provides a graphical illustration of this problem.

The Lagrangian method can be used to solve the household's problem. The Lagrangian can be specified as follows:

$$\mathcal{L} = \phi \log(c_A - \overline{c_A}) + (1-\phi)\log(c_N) - \lambda(p_A c_A + p_N c_N - w) \tag{28}$$

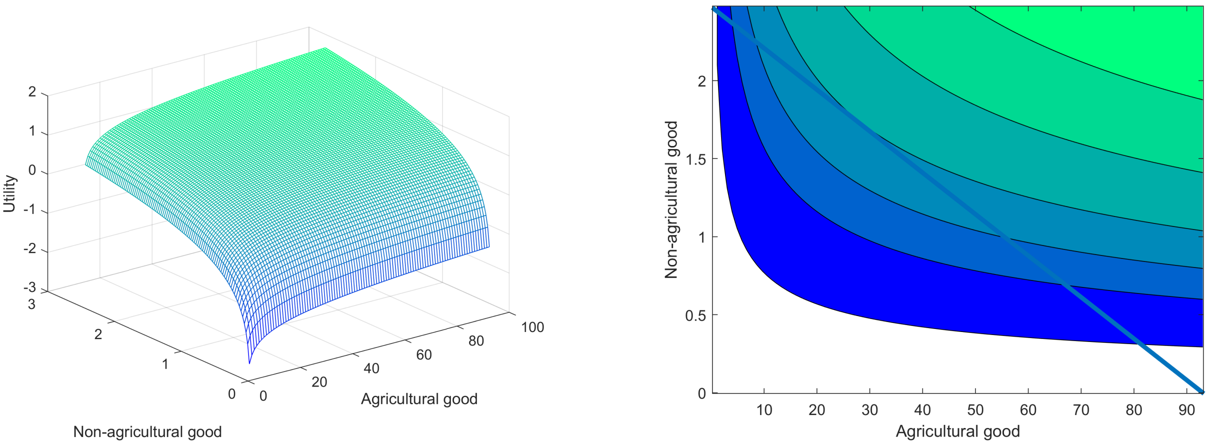
This yields the following three first-order conditions:

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial c_A} &= \frac{\phi}{c_A - \overline{c_A}} - \lambda p_A = 0 \\ \frac{\partial \mathcal{L}}{\partial c_N} &= \frac{1-\phi}{c_N} - \lambda p_N = 0 \\ \frac{\partial \mathcal{L}}{\partial \lambda} &= p_A c_A + p_N c_N - w = 0 \end{aligned} \tag{29}$$

Together, these first-order conditions can be solved for c_A and c_N to give demand functions for each consumption good:

$$c_A = \phi \frac{w - p_A \overline{c_A}}{p_A} + \overline{c_A} \tag{30}$$

$$c_N = (1 - \phi) \frac{w - p_A \overline{c_A}}{p_N} \tag{31}$$



(a) Utility function

(b) Indifference curves and budget constraint

Figure 25: Consumer's utility maximisation problem.

C.2. Firms

I assume the sector-specific firm profit maximisation problems for the agriculture and non-agriculture sectors A and N both take the form of a constant elasticity of substitution function:

$$\max_{M_s, L_s} p_s B_s \left(\eta_s M_s^{\frac{\sigma_s - 1}{\sigma_s}} + (1 - \eta_s) L_s^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} - p_M M_s - w L_s, \quad s = A, N \tag{32}$$

In this maximisation problem, η_s is the sector-specific motor vehicle share parameter, while σ_s represents the sector-specific elasticity of substitution between motor vehicle and labour inputs. Total factor productivity B_s also differs between the two sectors. This form of production function allows me to set constant sector-specific elasticities, σ_s, as part of the model calibration process. Figure 26 illustrates this production function.

The firm maximisation problem yields two first-order conditions:

$$\begin{aligned}
\frac{\partial \Pi_s}{\partial M_s} &= p_s B_s \eta_s M_s^{\frac{\sigma_s - 1}{\sigma_s} - 1} \left(\eta_s M_s^{\frac{\sigma_s - 1}{\sigma_s}} + (1 - \eta_s) L_s^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} - p_M = 0, \quad s = A, N \\
\frac{\partial \Pi_s}{\partial L_s} &= p_s B_s (1 - \eta_s) L^{\frac{\sigma_s - 1}{\sigma_s} - 1} \left(\eta_s M_s^{\frac{\sigma_s - 1}{\sigma_s}} + (1 - \eta_s) L_s^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} - w = 0, \quad s = A, N
\end{aligned} \tag{33}$$

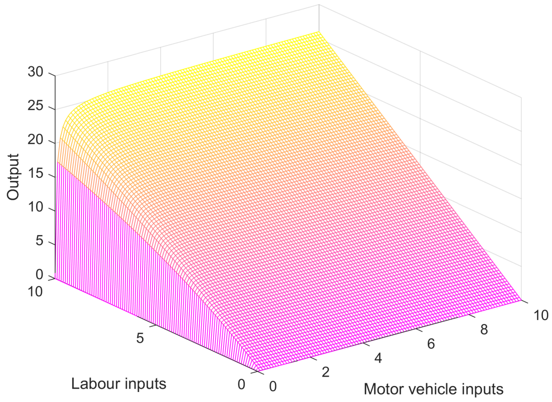


Figure 26: Firm's production function.

These first-order conditions can be divided by each other as follows:

$$\frac{p_M}{w} = \frac{p_s B_s \eta_s M_s^{\frac{\sigma_s - 1}{\sigma_s} - 1} \left(\eta_s M_s^{\frac{\sigma_s - 1}{\sigma_s}} + (1 - \eta_s) L_s^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}}}{p_s B_s (1 - \eta_s) L^{\frac{\sigma_s - 1}{\sigma_s} - 1} \left(\eta_s M_s^{\frac{\sigma_s - 1}{\sigma_s}} + (1 - \eta_s) L_s^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}}}, \quad s = A, N \tag{34}$$

An input demand function for M_s in terms of L_s can then be derived by simplifying this equation and solving for M_s:

$$M_s = \left(\frac{w}{p_M} \right)^{\sigma_s} \left(\frac{\eta_s}{1 - \eta_s} \right)^{\sigma_s} L_s, \quad s = A, N \tag{35}$$

Meanwhile, I assume the firm profit maximisation problem for the intermediate motor vehicle sector M takes a linear form:

$$\max_{L_M} p_M B_M L_M - w L_M \tag{36}$$

In this sector, a representative firm operating in perfect competition takes the economy-wide wage rate w and the price of motor vehicles p_M as exogenously given and chooses a level of labour inputs L_M in order to maximise profit Π_M. Total factor productivity in this sector is given by B_M. This maximisation problem yields the following first-order condition:

$$\frac{\partial \Pi_M}{\partial L_M} = p_M B_M - w = 0 \tag{37}$$

This shows that $p_M B_M = w$ in my model.

C.3. Counterfactual 1: No structural transformation

In my first counterfactual model, I imposed that no structural transformation occurred in the economy. To achieve this, I merged the agriculture and non-agriculture sectors into a single final good sector as follows.

First, I again assume the consumer optimisation problem takes the form of a log utility function but with consumers simply choosing a level of consumption of the single non-agriculture good that maximises utility subject to their budget constraint:

$$\begin{aligned} \max_{c_N} \quad & \log(c_N) \\ \text{s.t.} \quad & p_N c_N = w \end{aligned} \tag{38}$$

This optimisation problem yields a more straightforward demand function than my main model:

$$c_N = \frac{w}{p_N} \tag{39}$$

Second, I assume the non-agriculture firm profit maximisation problem again takes the form of a constant elasticity of substitution function, while the firm profit maximisation problem for the intermediate motor vehicle sector M continues to take a linear form. Given the absence of a separate agriculture sector, the agriculture-related parameters B_A, ϕ, $\overline{c_A}$, σ_A and η_A all disappear from the model, while all other parameters remained.

Therefore, it was necessary to re-calibrate the remaining parameters in this one-sector model using the same data and methodology as with my main model, but with agriculture and non-agriculture sectors combined into a single 'non-agriculture' sector in terms of inputs and value added. Table 12 reports these re-calibrated values.

Table 12: Re-calibrated one-sector parameter values: main panel aggregates 1995-2016

Parameter	Parameter description	Value	Target
$L_0, B_{s,0}$	Labour force and productivity, 1995	1.000	Normalisation
g_L	Labour force growth rate	1.004	Labour force growth
g_N	Non-agriculture TFP growth	2.777	Productivity growth in N
g_M	Motor vehicle TFP growth	1.603	Productivity growth in M
σ_N	Non-agriculture elasticity of substitution	0.604	Vehicle inputs in N, 2016
η_N	Non-agriculture vehicle share parameter	0.006	Labour share in M, 1995

TFP denotes total factor productivity. Annualised growth rates reported as percentages.

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