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Why is Japan's carbon emissions from road transportation declining?

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ABSTRACT

Average fuel efficiency of vehicles improved substantially over the last three decades in Japan. Yet, the carbon emissions from on-road passenger vehicles continued to increase until 2000, and then turned to a steadily declining trend. We empirically investigate this disparity. To that end, we apply an analogue of the Copeland-Taylor decomposition, combined with an empirically estimated behavioral model of car ownership and utilization choice, to economically decompose vehicle carbon emissions into the scale, composition, and technique effects over our study period, 1990–2015. We find that exogenous demographic changes such as population size, driver's license holdings, or labor migration across regions can only explain this disparity partially. After accounting for endogenous changes in household's geographically-explicit transport demand by the estimated behavioral model, the predicted emissions match the time path of the observed emissions surprisingly well. Of all the factors in the behavioral model, the fuel cost per unit of driving accounts for the largest share of the total variation in the observed emissions. Our result indicates that 60% of the technique effect is offset by the perverse effect of induced transport demand due to the lower fuel cost. Importantly, the induced demand comes from both the intensive margin (driving) and the extensive margin (car ownership).

1. Introduction

Road transport is the second largest contributor of global GHG emissions today, accounting for roughly 16% of global GHG emissions and 22% of global carbon dioxide (CO_2) emissions (Our World in Data, 2020). How best to control carbon emissions from driving of private vehicles continues to be a daunting and important task for policy makers worldwide (Anderson et al., 2011; Knittel, 2012). This manuscript attempts to draw some useful insight for transport-related climate mitigation policies by analyzing 25-years of data in Japan. In Japan, the average fuel economy ratings of passenger vehicles (cars and vans) have dramatically improved from 1990 to 2015 — by a roughly constant rate of 13% each five-year period. Yet, vehicle CO_2 emissions from households sharply increased from 1990 to 2000, after which they began to decline dramatically. Fig. 1 demonstrates this striking discrepancy between the trend in fuel-economy technology and that of vehicle CO_2 emissions over this period. The Japanese Ministry of Land, Infrastructure, Transport and Tourism (MLIT) and industry reports often claim that the emissions decline since 2000 is largely due to the improvement in fuel-efficiency technologies (MLIT, 2021; Japan Automobile Manufacturers Association, 2010). However, such an explanation fails to explain this disparity we observe in Fig. 1, leaving us the puzzle: What then explains the disparity between the two trends?

With this question in mind, this manuscript attempts to *economically* decompose vehicle CO_2 emissions from households over the 25-year period from 1990 to 2015, *endogenizing* consumer's car ownership and utilization choices.[1] Our approach is similar, in spirit, to Copeland and Taylor (1994; 2003) and Shapiro and Walker (2018) in that the emissions are conceptually decomposed into three terms: scale, composition, and technique effects. We, however, differ substantially from them on several important accounts. First, we only study road transportation, and we do not explicitly build a general-equilibrium model of that sector. Instead, we only model consumer's car ownership and utilization decisions explicitly, taking car prices, car model offerings, gasoline

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[1] We only analyze the CO_2 emissions from on-road passenger vehicles owned by households because we do not have access to detailed data that would allow us to economically decompose CO_2 emissions from commercial vehicles or other transport modes. For example, e-shipping is likely to be an important source of variation in CO_2 emissions from commercial vehicles, yet we don't have data to account for changes in its geographic distribution (at municipality level) over time. Nonetheless, we believe some of the underlying mechanisms in this paper (changes in demographics, price, income, fuel economy, product mix) are also important in understanding other transport-related CO_2 emissions.

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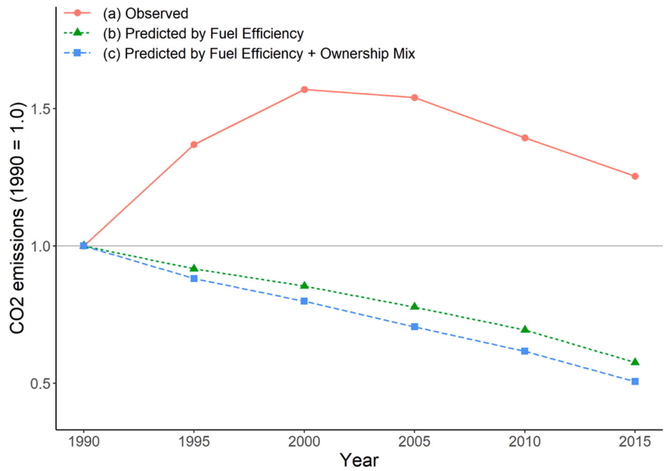

Fig. 1. CO_2 Emissions from On-road Passenger Vehicles in Japan, 1990–2015. *Note*: The figures include on-road CO_2 emissions from vehicles held by households only, excluding those from non-commercial vehicles. (a) Actual observed CO_2 emissions, (b) CO_2 emissions predicted from fuel efficiency improvements, holding other factors fixed, and (c) CO_2 emissions predicted from fuel efficiency improvements and car holding mix of *kei-cars* versus regular cars, holding other factors fixed.
Source: Greenhouse Gas Inventory Office of Japan (2022) and Author's calculation.

prices, and other economic factors as exogenously fixed at the observed levels. Hence, our model does not account for the changes in the economy-wide sector composition over time. Second, we account for changes in the *geographic* distribution of households' endogenous automobile demand over time. Japan has experienced rapid demographic changes during the study period: The overall population peaked in 2008 while the share of the elderly (age 65 or above) increased from 12.1% in 1990 to 26.6% in 2015. Along with this demographic change, Japan has also witnessed a substantial migration of households during the same period. For example, the share of population living in six largest cities increased from 15.4% in 1990–16.9 in 2015. This change in the geographic distribution of households alone can potentially explain the observed patterns in vehicle CO_2 emissions because the demand for vehicle transport differs substantially between urban and non-urban areas due to differences in public transit availability or other city structures.

With these in mind, we first start with the *statistical* decomposition of the vehicle CO_2 emissions in a manner analogous to Copeland and Taylor (1994), yet tailor the definition of the scale, the composition, and the technique effects into our settings. We define the scale effect as the effect directly driven by changes in the *total* driving demand — i.e., changes in the total vehicle kilometers travelled summed over all regions in Japan. The composition effect is defined as the effect of changes in the composition of driving demand across households, regions, and/or types of car holdings. The technique effect is then defined simply as the effect of changes in fuel efficiency technologies, which determines CO_2 emissions per unit of driving, holding constant the CO_2 emissions rate per unit of energy consumption. Hence, by definition, the scale and the composition effect must explain the puzzling discrepancy mentioned above.

We then attempt to *economically* decompose the scale and the composition effects into *exogenous* and *endogenous* terms. To do so, we borrow from the discrete-continuous choice model developed and estimated in Konishi et al. (2021). The model is estimated on the detailed household-level dataset from a national internet survey conducted in 2016. The model builds on the conventional discrete-continuous choice framework (e.g., Dubin and McFadden, 1984; Goldberg, 1998; West, 2004; Bento et al. 2005, 2009; Jacobsen, 2013), but is unique in that it allows for parameters to depend not only on household and product attributes but also on regional attributes (public transit density, in particular). Hence, the model allows us to predict location-specific vehicle ownership and utilization rates as well as how they respond to changes in spatial demographic distribution over time.

We use census and GIS data to construct the distributions of age, income, household size, and public transit density *at the municipality level*. Consumer's "choice set" is constructed and adjusted for each period (in a 5-year interval), based on the available car offerings for each interval, using catalog data on car prices and car attributes (fuel economy) as well as gasoline prices. The predicted shares of different car models and predicted annual driving distance for each municipality are then multiplied by the number of households for that municipality. We treat the number of households in each municipality in each year as exogenous, and we fix them at the observed level. Consequently, in our model, total driving demand changes partly due to purely exogenous changes in demographics and partly due to endogenous behavioral responses to exogenous factors (e.g., car prices, car attributes, gasoline prices, household characteristics, changes in public transit availability).

We have three important findings. First, contrary to our expectation, demographic changes cannot fully explain the scale and the composition effects. Changes in the total number of households (or driver's license holders) and its spatial distribution across municipalities over time can only explain about half of the gap between the two trends in Fig. 1 over the 25-year study period. Second, we find that much of the remaining variation can be explained by endogenous demand responses due to improved fuel efficiency technology (roughly 87.2% of the gap); and if they were not considered, the prediction errors would be two to ten times larger. In other words, we can only explain the observed vehicle CO_2 emissions after accounting for endogenous demand responses. It is important to emphasize here that we do *not* obtain this result by construction — ours is not the *statistical* (or mechanical) decomposition of total variation; the endogenous term is predicted from the discrete-continuous choice model estimated on a separate study sample, not fit to the observed trends in CO_2 emissions. Third and most importantly, of the endogenous demand responses, fuel economy improvements have the largest explanatory power, accounting for 16.9% of total variation. This means that, while improvements in fuel efficiency technology significantly reduce emissions *per unit* of driving, 60% of this reduction is offset by an increase in vehicle demand, in terms of both utilization and ownership, due to its effect of decreasing driving costs.

Our results have several important implications for optimal design of policies to control carbon emissions from road transportation. First, our results reinforce the key finding from the previous empirical studies on this topic, which echoes the conventional view held by many environmental economists: Optimal pricing of pollution, via the gasoline tax in this context, is critical, and without it, simply improving fuel efficiency of automobiles is unlikely to curtail vehicle carbon emissions effectively. We arrive at this with an approach quite different from the previous studies, however. The earlier studies estimate a behavioral model of household's demand for automobiles, either using cross-section survey data on car ownership/utilization (e.g., Goldberg, 1998; Bento et al., 2009; Jacobsen, 2013) or using a panel of sales data over a relatively short period (e.g., D'Haultfœuille et al., 2014; Konishi and Zhao, 2017; Reynaert, 2021), and then use the estimated model to simulate the economic impacts of counterfactual policies. In contrast, we take the 25-years of aggregate-level vehicle CO_2 emissions data in Japan, and use the micro-level (empirically estimated) behavioral model, in combination with the Copeland-Taylor decomposition, to test how much of the total variation in emissions over the 25-year period can be explained by the model. Thus, our approach is similar, at least in spirit, to Shapiro and Walker (2018).

Second, our work identifies two different sources of the perverse effect of lowering the user cost of driving (i.e., dollar per unit of driving distance), often known as the Jevons paradox. The empirical literature often focuses on the *rebound effect* of energy-saving investments (e.g., Small and Van Dender, 2007; Jacobsen, 2013; Linn, 2016; Yoo et al., 2019; Craglia and Cullen, 2020). That is, higher fuel efficiency reduces per-unit cost of driving, and hence may induce more driving. We also find evidence for another type of induced demand, however. That is, higher fuel efficiency increases the expected payoff from owning a vehicle *relative to* other transportation mode, and hence may induce a higher rate of car ownership. We find that both effects are important in explaining the vehicle emissions trend. This second type of induced demand is implicit in all studies cited above. However, ours is probably the first to quantify its sizable impact of the Jevons paradox over such a long-run time span.

Lastly, however, we also find that when the scale effect (or the effect of population size) tapers off, the technique effect (or the effect of technology improvement alone) starts to dominate. Although we do not formally explore its implication, this may imply that the effectiveness of technology-based regulation (e.g., fuel-economy regulation) may depend on whether the *potential* demand is sufficiently saturated in a given country. In our context, the sizable Jevons effect arises precisely because the lower utilization cost due to the technological progress induces the higher demand for automobiles. In an economy with the flattening size of potential drivers, however, this Jevons effect may not be large because the inducible potential demand may be limited. In fact, we do observe similar U-shaped CO_2 emissions trends for on-road transportation in Europe and in the United States. In contrast, in countries like India and China where there is still likely to be large unexploited demand for automobiles, incentive-based policies (e.g., carbon/gasoline taxes), which would raise the utilization cost, is likely to be more effective in reducing transport-related CO_2 emissions than a technology-based regulation (e.g., fuel-economy regulation or subsidy to promote fuel-economy technologies).

This paper complements three strands of literature. First, there is a large literature that investigates, theoretically and empirically, the efficiency properties of alternative policies to control emissions from road transportation (Fullerton and West, 2002, Huse and Lucinda, 2014, Klier and Linn, 2015, Yan and Eskeland, 2018, Chen et al., 2021, and other papers cited in Anderson et al., 2011; Knittel, 2012; or Anderson and Sallee, 2016). Second, there are empirical studies that attempt to quantify the economic and environmental impacts of fuel-economy regulation using the discrete-continuous choice model similar to ours (e.g., Goldberg, 1998; Jacobsen, 2013; Klier and Linn, 2012; Reynaert, 2021). Third, there is also a large literature in the non-economic journals that use statistical factor decompositions to explain changes in CO_2 emissions over time (see papers cited in Shiraki et al., 2020; Robaina and Neves, 2021; Long et al., 2021). The approach we take in this paper builds on findings from all these strands of literature. We, however, take a step further. We use the empirically estimated behavioral model of discrete-continuous choice of car ownership and utilization, apply it in the Copeland-Taylor type factor decomposition, to understand the economic factors behind the long-run time path of CO_2 emissions from road transportation over the 25-year period, 1990–2015.

2. Background and motivation: A *statistical* decomposition

In 1990, 49.5 million tons of CO_2 was emitted from on-road vehicles in Japan. The vehicle CO_2 emissions continued to increase and peaked in 2000 at 77.7 million tons in 2000 (57% increase from the 1990 level). The emissions then declined consistently throughout the remaining period. In 2015, the vehicle CO_2 emissions was roughly 62.1 million tons (10% decrease from the 2010 level, but 1.25 times the 1990 level). On the other hand, the average fuel efficiency of owned vehicle fleet has substantially improved from 1990 to 2015. For example, the average fuel efficiency ratings of gasoline cars with weight between 1100 kg and 1200 kg (calculated as the average of owned vehicles) improved by almost 75% from 9.7 km/L in 1990–17.0 km/L in 2015. This *vehicle-specific* fuel efficiency improvement may understate the true technical change, however. New, improved car models have been introduced throughout the period, and they rapidly increased their market shares over time. For example, the market share of fuel-efficient *kei-cars* increase from 6.2% in 1990 to 34.7% in 2015, and the share of hybrid vehicles also increased from 0.5% in 2005 to 9.6% in 2015.

Fig. 1 visualizes these trends. In the figure, three CO_2 emissions time series are plotted. The red line is the observed vehicle CO_2 emissions, normalized against the 1990 value. The green dashed line plots the counterfactual vehicle CO_2 emissions if all other factors were held fixed at the 1990 level, but the fuel efficiency ratings of all vehicles change as observed. The blue dashed line plots the counterfactual emissions if the ownership mix also change as observed. The figure demonstrates that the product mix widens the gap between the observed CO_2 trend and the technique effect. Our goal in this paper is to empirically investigate the factors that explain this gap.

To do so, we start by presenting a *statistical* decomposition of vehicle CO_2 emissions over the study period, 1990–2015, following Copeland and Taylor (1994) and Shapiro and Walker (2018). In the original definition, the scale effect refers to the change in emissions caused solely by scaling up the size of the economy, the composition effect refers to the change in emissions caused solely by changes in the composition of output across manufacturing industries, and the technique effect refers to the change in emissions caused solely by changes in emissions intensity per unit of production or consumption within an industry. We tailor this line of logic to our setting, and define the analogue of Copeland-Taylor decomposition of the vehicle CO_2 emissions Z as follows:

$$Z = X\sum_s \kappa_s e_s = X\kappa' e \tag{1}$$

where X is total travel demand, κ is vehicle type share, and e is fuel efficiency technology (or emission intensity). The change in emissions dZ/Z is then expressed as the sum of three terms representing the scale (dX/X), composition ($d\kappa/\kappa$), and technique effect (de/e):

$$\frac{dZ}{Z} = \frac{dX}{X} + \frac{d\kappa}{\kappa} + \frac{de}{e} \tag{2}$$

To what extent does this decomposition help us (or does not help us) understand the gap? As a first step, we further decompose total driving demand X into two terms: $X = N \times x$, where N is the number of households and x is the travel demand per household. For the moment, let us fix the per-household travel demand x at the 1990 level. Then, total travel demand must change proportionally to the number of households.

As shown in **Panel A of** Fig. 2, the number of households grew at a faster rate than the population itself over the study period. This occurs not only because more people remain unmarried, forming single-person households, but also because of the so-called "nuclearization of families" — traditionally, married couples used to live in the same house with their parents, but are now increasingly less likely to do so today. Because car ownership and utilization decisions are often made at the household level in Japan and elsewhere, the number of households is an important determinant of the total travel demand. Furthermore, the figure also indicates that the number of households with at least one driver's license holder increased even faster than the number of households itself. This reflects the fact that holding a driver's license constitutes a certain social status in Japan — the driver's license is commonly used as an identification for various administrative purposes, and hence, non-driving individuals still obtain driver's license just as an identification card. In **Panel B of** Fig. 2, we plot the counterfactual vehicle CO_2 emissions incorporating the scale effect and the technique effect, taking these alternative measures of N as the exogenous change in the total travel demand $X = N \times \bar{x}$, but holding the per-household travel demand at the 1990 level $\bar{x}$. From this exercise, we see that the change in the number of households with driver's license generates an inverted U-shaped relationship that comes closer to the observed emissions trend.

By construction, then, the remaining gap must come from the composition effect (if we are willing to assume that the per-household

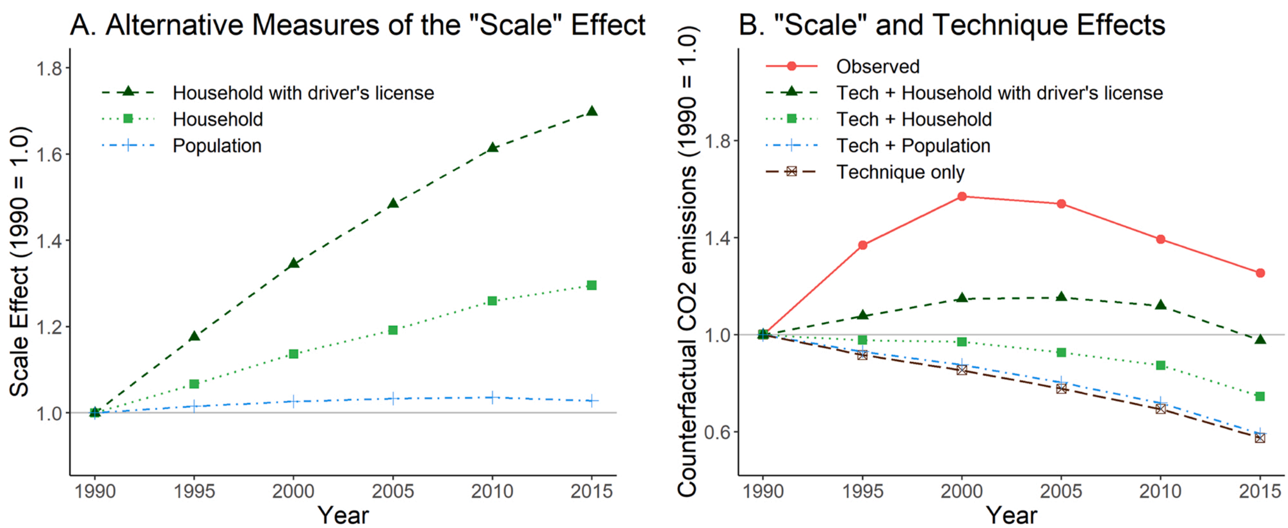

Fig. 2. "Scale" Effect of Vehicle CO_2 Emissions in Japan, 1990–2015. *Note*: In Panel B, we calculate the counterfactual CO_2 emissions with the three types of exogenous scale variation (N) presented in Panel A on top of technique effect and the composition change (κ) is not taken into account.

travel demand stays constant). This raises another question, however. As we have already seen from Fig. 1, the compositional change of different types of vehicles tend to decrease the vehicle CO_2 emissions, and hence, it should bring down (rather than bring up) the counterfactual emissions trend. Hence, we must seek another kind of composition effect. In Shapiro and Walker (2018), the composition effect is defined as either the changes in resource allocation across industries or in product mix within the industries. In our setting, there is no sectoral reallocation, as we focus only on the road transportation sector. There is, however, a natural analogue to "sectors" in our setting. Different areas have different degrees of economic development with varying levels of public transit networks. Therefore, if the composition of population across regions changes, this alone may change the emissions path in an ambiguous way.

To get a sense of the direction of this composition effect, **Panel A of** Fig. 3 compares the geographical distribution of population in 2015 against that in 1990. For ease of interpretation, we use a measure of public transit density of railroad infrastructure as in Konishi et al. (2021). We see that a non-negligible share of population moved away from rural areas with low public transit density to urban/suburban areas with higher public transit density. To estimate the magnitude of this effect, we re-define κ_s as the population share of each municipality s, rather than the share of vehicle type, in Eq. (1). In **Panel B of** Fig. 3, we plot the counterfactual CO_2 emissions incorporating this type of composition effect on top of the technique effect. To calculate this emissions path, we use the observed number of households with driver's license in each municipality N_s, and multiply this by average per-household transport demand $\bar{x}_s$ for each municipality (held constant). By construction, this emissions path incorporates all three effects. However, we see there is still a large discrepancy between this emissions path and the observed CO_2 emissions. The gap between the two trends is still only explained by 1/3 to at most 1/2 by the factors considered so far.

The fact that neither of the decomposition exercises so far can reproduce the observed emissions path means that we are not properly accounting for either the scale effect or the composition effect or both. What is missing so far is the transport demand of each household x, which we hold constant. In reality, the transport demand may change endogenously over time, presumably in response to changing demographics and economic environments. For example, the increase in

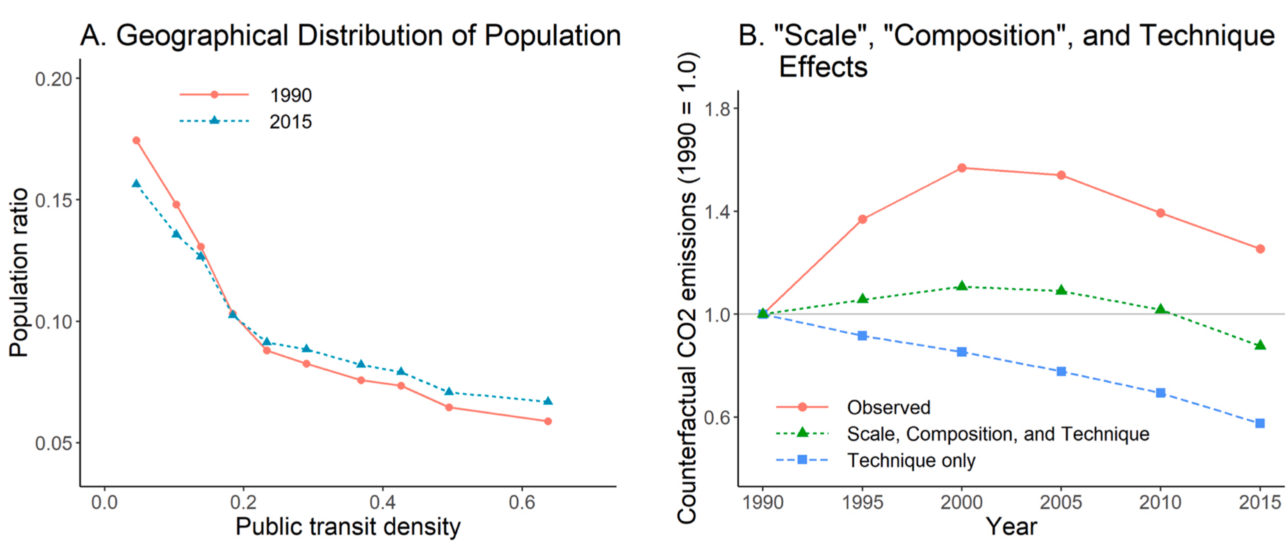

Fig. 3. "Composition" Effect of Vehicle CO_2 Emissions in Japan, 1990–2015. *Note*: Panel A shows the average of population ratio in each public transit density bin. Panel B shows the counterfactual CO_2 emissions considers the composition effect on top of scale and technique effect in addition to actual observed emissions and emissions predicted by technique effect alone.

the number of single-person households or single-family households implies that both the average household size and the average household income are smaller, which would decrease the household's demand for car ownership and utilization ceteris paribus. On the other hand, the substantial improvement in the fuel economy technology implies that the utilization cost of vehicles is lower, which would increase the household's demand for car ownership and utilization. There are other factors that are unaccounted for so far that may affect the endogenous transport demand x. We thus attempt to account for such factors in more depth in the next section.

3. Model

We start by re-writing the decomposition Eq. (1), re-defining terms. Let N be the total number of households with at least one driver's license holder, which we interpret as the potential size of the road transportation sector per our discussion in **Section 2** . Let κ_r denote the share of such households in each municipality r. Let x_{jr} be the "average demand for road transport" by a household holding vehicle type j and residing in municipality r. We define x_{jr} more precisely shortly below. The emissions intensity e_j is defined as the emissions per unit of fuel consumption (CO_2/L) divided by fuel efficiency (km/L). We can then write the total vehicle CO_2 emissions as:

$$Z = \sum_r \left[\kappa_r N \left(\sum_j x_{jr} e_j \right) \right] \tag{3}$$

Note that Eq. (3) is essentially an identity in theory. That is, the observed CO_2 emissions in the left hand side must coincide with the right hand side. Because we have observed values for N, κ_r, and e_j, we could obtain the estimates of x_{jr} by fitting (or calibrating) the data, in theory. There are two problems with this approach. First, the values of x_{jr} are not identifiable in this approach because the number of "estimands" x_{jr} far exceeds the number of observations. Second, even if we obtain the estimates of x_{jr} this way, they are not amenable to economic interpretation, which we can bring to policy implications.

We, therefore, take an alternative route. We use the discrete-continuous choice model estimated in Konishi et al. (2021) to predict the transport demand per household for each municipality. More specifically, the predicted transport demand $\widehat{x}_{jr}$ is given by:

$$\widehat{x}_{jr} = \widehat{\lambda}_{jr}(\boldsymbol{w}_{jr}) \times \widehat{\nu}_{jr}(\boldsymbol{w}_{jr}) \tag{4}$$

where $\widehat{\lambda}_{jr}$ and $\widehat{\nu}_{jr}$ are, respectively, the predicted probability of owning a vehicle type j and the predicted annual vehicle kilometers travelled (VKT) by a household living in r given the vector of observed attributes $\boldsymbol{w}$ of cars, households, and regions, and $\widehat{\nu}_{jr}$ is the predicted annual vehicle kilometers travelled by the same household. Estimation of the discrete-continuous choice model is done on a sample of roughly 100,000 households from a national internet survey conducted in 2016. The estimated model has the following features: (a) Each household is assumed to own at most two cars. The model accounts for the correlation between choices of the first and the second cars by adding the terms that capture utility from having a particular combination of vehicles; (b) it allows for the parameters of indirect utility to depend explicitly on a measure of public transit density, generating realistic substitution patterns that are explicitly linked to public transit; and (c) it applies the Dahl (2002)'s control function approach to control for correlation in the error terms in the ownership and driving equations.

Given the parameter estimates from Konishi et al. (2021), we compute the predicted values of $\widehat{\lambda}_{jr}$ and $\widehat{\nu}_{jr}$ as follows. We first start by defining the choice set C_t for each year t, from which households choose a car portfolio to own. This choice set is defined as the set of different vehicle categories j's, each having a unique vector of product attributes $\boldsymbol{a}_{jt}$. That is, $C_t \equiv \{\boldsymbol{a}_{jt}\}_{j\in J_t}$. We adjust the choice set for each period (in the 5-year interval) since the types of vehicles available J_t as well as their attributes $\boldsymbol{a}_{jt}$ in the market change over time. We then use the estimates of structural parameters from Konishi et al. (2021) and calculate $\widehat{\lambda}_{jr}$ and $\widehat{\nu}_{jr}$ as follows.

$$\widehat{\lambda}_{jrt} = \int \Pr\left(u_j(\boldsymbol{a}_{jt}, \boldsymbol{s}_{rt}, \boldsymbol{h}; \widehat{\boldsymbol{\beta}}) \geq u_k(\boldsymbol{a}_{kt}, \boldsymbol{s}_{rt}, \boldsymbol{h}; \widehat{\boldsymbol{\beta}}), \forall k\right) d\mu_{rt}(\boldsymbol{h}) \tag{5}$$

where u_j is the indirect utility of owning vehicle portfolio j with the parameter estimates $\widehat{\boldsymbol{\beta}}$, $\boldsymbol{s}_{rt}$ is the vector of attributes in municipality r, $\boldsymbol{h}$ is the vector of household attributes such as household size and household head's gender, and μ_{rt} is the empirical distribution of household attributes in municipality r in year t.

$$\widehat{\nu}_{jr} = \int E\left[d(\boldsymbol{a}_{jt}, \boldsymbol{h}, \boldsymbol{s}_{rt}; \widehat{\boldsymbol{\gamma}})\right] d\mu_{rt}(\boldsymbol{h}) \tag{6}$$

where d is the empirical driving distance equation with the parameter estimates $\widehat{\boldsymbol{\gamma}}$. The details on how we construct the choice set C_t as well as the sketch of how Konishi et al. (2021) obtain the parameter estimates $\widehat{\boldsymbol{\beta}}$ and $\widehat{\boldsymbol{\gamma}}$ are available in the Online Appendix.

Given (3) and (4), we can re-define the decomposition as follows:

$$\begin{aligned} \frac{dZ}{Z} &= \frac{dN}{N} + \frac{dx}{x} + \frac{d\kappa}{\kappa} + \frac{de}{e} \\ &= \left(\frac{dN}{N} + \frac{d\kappa}{\kappa} + \frac{de}{e}\right) + \left(\frac{d\nu}{\nu} + \frac{d\lambda}{\lambda}\right) \end{aligned} \tag{7}$$

The first set of parentheses in Eq. (7) corresponds to the scale, composition, and technique effects that vary exogenously due to demographic and technological changes, and the second set corresponds to the scale and composition effects that are explicitly modeled to vary endogenously in response to exogenous factors (i.e., changes in car prices, car attributes, gasoline prices, household attributes, and public transit density).

In theory, the terms in the second parenthesis in Eq. (7) should explain the remaining gap we observe in Fig. 3. *Empirically*, however, the predicted values of $\widehat{\lambda}_{jr}$ and $\widehat{\nu}_{jr}$ from the *estimated behavioral model* need not because the model is not directly fit to the observed emissions path for Z, and is instead estimated on the survey sample we obtained elsewhere. The question is, to what extent the estimated behavioral model can explain the observed path for $x = \lambda \times \nu$ (or equivalently the gap we observed in Fig. 3).

4. Data

We use three sets of data for our analysis. All data are compiled every five years from 1990 to 2015 expect for the second set of data. The Online Appendix provide more detailed explanation of the data and variables used in the analysis.

The first is demographic data. We obtain census data on the total number of households by household size at the municipality level from the National Census, Statistics Bureau. In 1990, we do not have data on the number of households by municipality, and hence, the 1990 values are linearly imputed from 1995/2000 data. The number of driver's license holders is available from the Operating License Statistics, National Police Agency, but only at the prefecture level. Hence, we calculate the driver's license holding rate by gender at the prefecture level, and apply the same holding rates equally to all municipalities within the same prefecture to estimate the driver's license holding rate per household in each municipality in each year. These demographic data are also used to produce statistical decompositions in Figs. 1–3.

The second set of data are the parameter estimates $(\widehat{\boldsymbol{\beta}}, \widehat{\boldsymbol{\gamma}})$ of the discrete-continuous choice model from Konishi et al. (2021). One set of parameters are those that define the indirect utility function for car ownership. Another set of parameters are those that define the vehicle kilometers traveled given the choice of car holdings. The estimation of the parameters is done on the national internet survey data conducted in 2016, which contains detailed information on car ownership/utilization, geographic identifiers of residence as well as other socioeconomic characteristics of roughly 100,000 households in Japan. The survey data are combined with the car catalog data from Carsensor.net and regulatory information on car taxes and other incentives from the Ministry of Land, Infrastructure, Transport and Tourism (MLIT).

The third set of data are inputs ($\boldsymbol{a}_{jt}$,$\boldsymbol{h}$,s_{rt}) for the estimated behavioral model to predict the average household travel demand in Eqs. (4)–(6) for each municipality in each year.

Product Attributes in the Choice Sets $\boldsymbol{a}_{jt}$: For fuel efficiency, fuel type, and vehicle weights, we use catalog data from greeco-channel.com, which provides a comprehensive collection of characteristics of all vehicles sold in Japan. For car prices, we use the price index for each car-type obtained from the Retail Price Survey (Statistics Bureau). We calculate the fuel cost per unit of driving as YPK (yen per kilometer of driving distance) using the fuel efficiency ratings and the gasoline price obtained from the Retail Price Survey.

Empirical Distribution of Household Attributes $\boldsymbol{h}$: To construct the empirical distribution of household income by household size, we use data from the Family Income and Expenditure Survey (Statistics Bureau). Since household income by household size were not surveyed in 1990 and 1995, however, we estimate incomes by household size in 1990 and 1995 by extrapolating using the rate of change in average income obtained from the Statistical Survey of Actual Status for Salary in the Private Sector (National Tax Agency).

Municipality-level Public Transit Density s_{rt}: We calculate the public transit density index for each municipality, following Konishi et al. (2021), using the GIS data on railroad networks and railroad stations available from MLIT's National Land Numerical Information download service. This density index is defined as an average of two indices: the ratio of the area within a 15-minute walk to a station in inhabitable areas; and the ratio of railroad lines to the area. It shows the accessibility and usefulness of the public transportation infrastructure of railroads.

Fig. 4 plots the time paths of the mean values of these attributes that enter the behavioral model (normalized against the 1990 level). The figure demonstrates that the attributes of cars in the choice set have changed much more than the attributes of households or public transit availability. For example, the average car price (after adjusted for CPI) more than doubled from 1990 to 2015 while the average fuel economy (measured in yen per kilometer of driving) improved roughly at the same rate. This is consistent with the economic theory that the price of

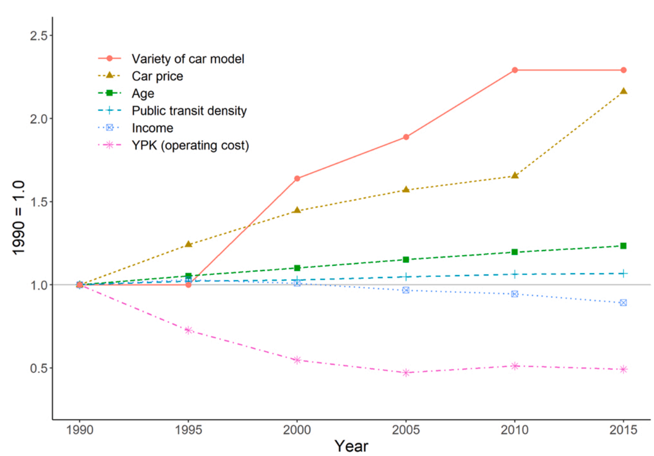

Fig. 4. Changes in the Key Variables in the Behavioral Model. *Note*: Variety of car model is the number of vehicle types available in the choice set. Household income is the average household income for two-person households. YPK is that of the mid-weight regular car. Public transit density index is the average over all municipalities.

cars must reflect the discounted economic value of savings in fuel consumption. On the other hand, the average household income (after adjusted for CPI) declined slightly while the average public transit density moderately increased over the same period. We expect, therefore, that if the behavioral model has any explanatory power for the remaining gap in Fig. 3, it must come from the ability to predict the behavioral responses to the changes in the attributes of cars in the choice set.

5. Result

We first present the results in a manner amenable to direct comparison with Figs. 1–3. That is, **Panel A of** Fig. 5 plots four counterfactual vehicle CO_2 emissions trends, *incrementally* adding each of the effects in Eq. (7), along with the actual emissions trend, all normalized against the values in 1990. The dashed line with the triangle marker represents the vehicle CO_2 emissions that would have occurred if only the technique effect occurred — i.e., the fuel efficiency ratings of vehicles change as observed, yet all other factors are fixed at the 1990 level. The dashed line with the square marker adds, on top of the technique effect, the exogenous scale effect — i.e., the effect of changes in the total number of households with driver's license, holding the other factors constant. The dashed line with the plus marker then adds the exogenous composition effect — i.e., the effect of households' migration across

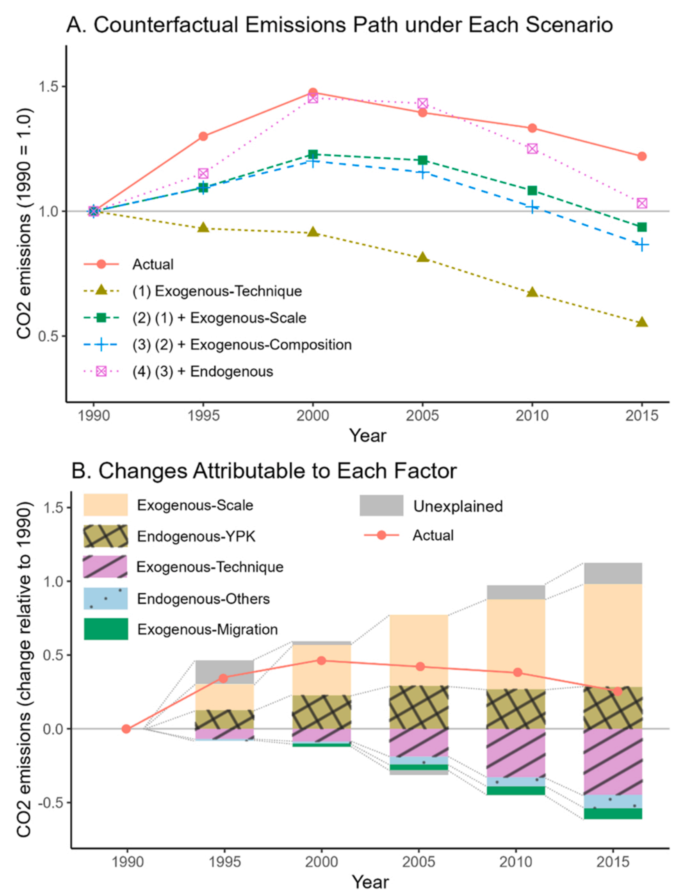

Fig. 5. Economic Decomposition of CO_2 Emissions from On-road Passenger Vehicles in Japan, 1990–2015. *Note*: Panel A shows the predicted CO_2 emissions when the following factors are incrementally taken into account: (1) fuel efficiency technology as exogenous technique effect, (2) the number of households with driver's license as exogenous change in scale, (3) migration as exogenous change in composition, and (4) change in driving demand per household calculated by the behavioral model as endogenous change in scale. In Panel B, 'Unexplained' is defined by the gap between the actual emission and the emission predicted by all factor (line (4) in the Panel A).

municipalities. Hence, by construction, these three lines correspond to the first three (exogenous) terms in Eq. (7), and are essentially the same as the counterfactual trends in Figs. 1–3. Finally, the dotted line with the square marker adds the predicted travel demand from the behavioral model on top of these effects.

We can see that the line comes remarkably close to the observed emissions path, despite the fact that the predictions are made from the microeconometric behavioral model, not directly fit to the aggregate level data. We do see relatively large errors in 1995 and 2015. We suspect that the prediction error in 1995 occurs because we had to use the imputed values for the municipality-level population for 1995 due to the lack of data. For 2015, we are not sure of the reasons for the prediction error, but we suspect that it might have to do with the fact that the gap between catalog-based versus actual on-road fuel efficiency has widen over the last decade (Tanaka, 2020), possibly due to manipulation of fuel efficiency ratings by car makers known as “gaming” (Reynaert and Sallee, 2021). In fact, our prediction matches the observed emissions in 2015 nearly perfectly if we apply their estimate of the performance gap found in the EU market.[2]

In **Panel B of** Fig. 5, we stack the change in CO_2 emissions attributable to each factor over time, this time by changing each factor one by one as observed while holding all other factors at the 1990 level. The figure visualizes what is already stated. The actual vehicle CO_2 emissions increased by 55.6% over the study period. The technique and (exogenous) composition effects would have caused the emissions to decline by 44.8% and 7.5%, respectively, failing to explain this trend. On the other hand, the (exogenous) scale effect alone would have increased the emissions by 69.7%, leaving another 38.2 ppt (= 55.6 − 44.8 − 7.5 + 69.7) as the remaining gap. Our estimated behavioral model predicts that the endogenous transport demand would have increased the CO_2 emissions by 19.4%, which explains roughly half of the remaining gap in 2015. The explanatory power of the behavioral model is particularly high in years between 2000 and 2010, during which we have more reliable data either on municipality-level population or fuel efficiency ratings as explained above. Furthermore, the fact that the model *underestimates* the actual CO_2 emissions means that we are missing some factors that induce a *higher* travel demand than predicted by the behavioral model. Thus, this result further signifies the importance of the puzzle we attempt to answer: Why the vehicle CO_2 emissions did not decrease as much as we expect from the sharp, consistent improvement in the fuel efficiency technology? Our behavioral model explains it quite well, albeit not perfectly so.

In Table 1, we also quantify the contribution of each factor as a percent of total variation for each year: For each factor $k \in K$,

$$\text{Share of contribution } by\ k \text{ in } year\ t = \frac{|\Delta_k^t|}{\sum_{k\in K} |\Delta_k^t|} \tag{8}$$

where Δ_k^t is the rate of change in emissions in year t relative to the 1990 level when only the factor k is varied. Table 1 reports the contribution shares for each year. The improvement in fuel efficiency technology (the technique effect) accounts for 25.2% of the total change in vehicle CO_2 emissions over the 1990–2015 period relative to the 1990 level while the increase in the number of households (the exogenous scale effect) and the migration (the exogenous composition effect) explains, respectively, 39.1% and 4.2%. The remaining 21.3% of the variation must be, by definition, accounted for the endogenous change in per-household transport demand per Eq. (7). Of this, the largest contributor turns out to be the change in the operating cost (YPK), which accounts for 15.9% of the total variation. To purge out the effect of changes in gasoline prices, we also calculate the counterfactual CO_2 emissions due to the endogenous transport demand in response to the change in YPK, *holding the gasoline price* at the 1990 level. It turns out this behavioral response alone can explain 15.1% of the total variation in the vehicle CO_2 emissions.

This implies two things. First, while improvements in fuel efficiency technology significantly reduce CO_2 emissions per unit of travel, *60% of this reduction is offset* by the corresponding increase in travel demand per household due to the lower operating costs induced by this technological change. This effect is large even compared to the exogenous scale effect. Second, the increase in gasoline prices since 2000 had the effect of partially offsetting the effect of improved fuel efficiency. The fuel efficiency improvement might have caused CO_2 emissions to increase more if the gasoline price did not increase. The result echoes the related empirical studies, which find the importance of gasoline prices in curtailing vehicle CO_2 emissions.

Lastly, we quantify the contribution of each of the demand factors in the behavioral model in Table 2. Recall that we endogenize the consumer’s transport demand in response to the following six factors: (a) car offerings (e.g., kei-cars vs. regular cars), (b) car prices, (c) operating costs (YPK), (d) household income, (e) public transit density, (f) others (household attributes such as age). In Table 2, we report the contribution of changes in each attribute holding other factors constant at the 1990 level in a manner analogous to Table 1, but this time, the share of contribution is calculated relative to the total variation in the endogenous transport demand. There are three messages from this table. First, the contribution of car prices is small, despite the fact that the magnitude of the increase in average car prices (after adjusted for CPI) is almost the same as that of operating costs (see Fig. 4). This is because the estimated elasticity is larger with respect to the operating cost than to the ownership cost. Second, the effects of household incomes and public transit density are also quite small. But this is expected because the changes in these variables are relatively small (Fig. 4). Third, the product offerings, particularly the introduction of more *kei-car* and hybrid car models, in the market have had non-negligible impacts both on ownership and utilization. This accounts for 11% of the total variation. While the effect is only under 15% of the effect of YPK, it does play a role in explaining changes in the per-household transport demand. These results signify the importance of accounting for endogenous demand responses to the technological change in fuel efficiency.

6. Conclusion

Average fuel efficiency of vehicle fleet in ownership has improved consistently throughout the last three decades in Japan. Yet, the total CO_2 emissions from on-road vehicles continued to increase from 1990 to 2000, after which the trend turned to a steady decline. Consequently, there is a large gap between the observed CO_2 emissions path and the counterfactual emissions path that would have occurred if all other economic factors stayed the same as the 1990 level while the fuel efficiency improvement follows the observed path. The manuscript attempts to empirically investigate what explains this gap.

We start by statistically decomposing the observed CO_2 emissions in Japan during our study period of 1990–2015, using an analogue of the decomposition framework by Copeland and Taylor (1994) and Shapiro and Walker (2018). The statistical decomposition takes (1) the size of population or the number of households as the scale effect, (2) reallocation of households across municipalities and the types of vehicles owned within municipalities as the composition effect, and (3) fuel efficiency improvement as the technique effect. We find that this statistical decomposition accounts for only half of the gap between the two trends.

To further explore the remaining variation, we combine the behavioral model of household’s car ownership and utilization decision with

[2] Reynaert and Sallee (2021) study the effect of the EU’s Fuel Economy (Carbon Emissions) Regulation, which started in 2007, on the performance gap between the catalog-based fuel efficiency ratings and the actual on-road fuel efficiency performance, using a panel of 250,000 drivers over 12 years in the Netherlands. They found that the catalog-based fuel efficiency improvements were only 30% effective, so that the remaining 70% is due to gaming.

Table 1
The Share of Contribution of Each Factor Relative to Total Variation in Vehicle CO_2 Emissions.

Change in emissions relative to 1990	Exogenous			Endogenous (x)		Unexplained
	Scale (N)	Composition (κ)	Technique (e)	YPK	Others	
1995	33.1% (+)	-	13.0% (–)	23.7% (+)	2.3% (–)	28.0% (+)
2000	48.1% (+)	3.1% (–)	12.1% (–)	31.6% (+)	1.9% (–)	3.2% (+)
2005	44.3% (+)	3.6% (–)	17.2% (–)	26.6% (+)	4.9% (–)	3.4% (-)
2010	43.4% (+)	4.3% (–)	23.3% (–)	18.9% (+)	4.3% (–)	5.8% (+)
2015	39.1% (+)	4.2% (–)	25.2% (–)	15.9% (+)	5.1% (–)	10.5% (+)

Note: The share of contribution is calculated as defined in Eq. (8).

Table 2
The Share of Contribution of Each Factor of the Behavioral Model.

Change in emissions due to endogenous demand (x)	Factors in the Behavioral Model					
	(a) Product mix	(b) Car price	(c) YPK	(d) Income	(e) Public transit	(f) Others
1995	0.0%	0.5% (–)	92.0% (+)	0.6% (+)	0.5% (–)	6.5% (–)
2000	6.5% (+)	0.4% (–)	86.2% (+)	0.1% (+)	0.3% (–)	6.4% (–)
2005	5.5% (+)	0.4% (–)	85.9% (+)	0.3% (–)	0.5% (–)	7.4% (–)
2010	12.2% (+)	0.4% (–)	77.1% (+)	0.4% (–)	0.6% (–)	9.3% (–)
2015	11.4% (+)	0.6% (–)	76.3% (+)	0.8% (–)	0.6% (–)	10.3% (–)

Note: The table reports the contribution of a two-person household living in a suburban, but the results are generally the same for other households. Product mix represents the set of products in the market.

the Copeland-Taylor decomposition framework. By construction of the decomposition, the remaining variation comes from changes in household's endogenous travel demand responses to changes to economic environment. The behavioral model uses the discrete-continuous choice model developed and estimated in Konishi et al. (2021). We construct the choice set of vehicles for each year from which households with different attributes residing in different municipalities choose a portfolio of vehicles to own and then choose an annual milage to drive. The estimated behavioral model is then applied to the choice set in each year (reflecting changing economic environment) to predict the average car ownership and utilization per household for each municipality every five year during the study period. Our results indicate that the endogenous demand responses explain the remaining variation in the observed vehicle CO_2 emissions surprisingly well (albeit limitations we discuss below); and if they were not taken into account, prediction errors would be several times larger. Importantly, the endogenous demand responses due to improved fuel efficiency technology accounts for as much as 87.2% of the gap between the two trends. Our results also substantiate the empirical relevance of the Jevons paradox over the long-time horizon: i.e., while improvements in fuel efficiency technology significantly reduce CO_2 emissions per unit of travel over the 25 years, 60% of this reduction is offset by the corresponding increase in travel demand per household due to the lower operating costs induced by this technological change.

These results may have important implications for policies targeted at transport-related carbon emissions in Japan and elsewhere. First, in theory, fuel-economy regulations are the second-best policy in settings where an efficient gasoline tax is not politically feasible. The limitation of such regulations is well established, both in theory and empirics — they can correct for externalities on extensive margin (car choice), but not on intensive margin (driving choice). Because fuel-economy regulations decrease the unit cost of driving, it may induce more driving — the effect known as the rebound effect. Our results suggest that there may be another demand-stimulating effect when we take into account the long-run dynamics. Fuel-economy regulations, if they work as intended, induce a faster rate of fuel-economy technology change. This will lower the costs of ownership and utilization. This may in turn stimulate demand for car ownership and utilization. Hence, the perverse effect of fuel-economy regulation may be even larger than previously thought when such dynamics are incorporated.

Second, Japan is not the only country where such a puzzling emissions trend is observed. For example, in the United States, CO_2 emissions from passenger transportation increased by a factor of 1.2 from 1990 to 2000, and then decreased by a factor of 1.1 over the following 10 years compared to 1990 (U.S. Bureau of Transportation Statistics, 2022). Similarly, CO_2 emissions from private cars in the EU also rose by 1.2 times from 1990 to 2000, peaked around 2004, and then began to decline afterwards (European Environment Agency, 2011). All three regions have similar fuel economy regulations, which are intended to stimulate fuel-economy technology improvements without harming automakers' profits. Our study is not meant to quantify the economic and environmental impacts of the fuel economy regulations, yet our results suggest that these inverted U-shaped trends in vehicle CO_2 emissions may be a natural consequence of fuel-economy regulations. Although a large number of studies have empirically investigated the economic and environmental effects of the fuel-economy regulations (e.g., Goldberg, 1998; Jacobsen, 2013; Reynaert, 2021), relatively little is done to investigate the long-run impacts of such regulations using long time-series data. Our findings suggest the need for empirical research that would incorporate the long-run dynamics of fuel-economy regulations more fully.

Lastly, we touch on several limitations of this study. First, the structural parameters of the discrete-continuous model used in this study is estimated on a single cross-sectional sample of households drawn from the internet survey conducted in 2016. This means that the identification of the model parameters relies on cross-sectional variations as of 2016. Yet, we apply the estimated model to predict behavioral responses over the 25-year study period, far back in time from the survey data. By this, we are implicitly assuming stationary behavioral responses over time. Second, to predict transport demand, we only consider the demand-side responses, not the supply-side responses such as strategic pricing or strategic product offerings. Third, there may be factors that we miss, yet are important in explaining the vehicle CO_2 emissions. For example, Tanaka (2020) find the evidence for non-negligible discrepancy between catalog and actual fuel economy. Despite these limitations, however, we believe that these missing factors are unlikely to significantly change the conclusions of the paper since the margin of change due to these factors is expected to be quite small, relative to the margin of change due to the other factors we incorporate in the analysis. For example, our analysis incorporates the inter-regional migration and other long-run demographic changes over the study period, yet we find the effect of these is quite small. Furthermore, the largest prediction failure occurs in 2015, in which the model *understates* the vehicle CO_2 emissions. This implies that we are missing factors that would predict *higher* transport demand or *higher* CO_2 emissions per unit of driving. Thus, decreased road congestion or increased prevalence of eco-driving would not explain the remaining gap. Exploring incorporating this aspect is important, but is left for future research.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.japwor.2023.101194.

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