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Carbon Dividends under Spatial Distribution of Automobile Demand

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【要旨】

We empirically examine the distributional consequences of income-based versus place-based recycling of carbon tax revenues when automobile demand varies substantially over geographic space. Using a large household dataset from Japan, we estimate a discrete-continuous choice model that parsimoniously accounts for the geographic distribution of incomes, public transit, and portfolio preferences. The model outperforms a naive random-coefficient model in explaining the observed spatial distribution of automobile demand, and allows us to estimate the price and income elasticities that vary by income and public transit density. The estimated model is used to simulate the distributional impacts of income-based versus place-based revenue recycling on carbon emissions and consumer welfare. Our results show the following: first, the improvement in consumer welfare from rebates substantially outweighs the increase in negative externalities from the rebound in carbon emissions; second, place-based recycling outperforms income-based recycling in mitigating welfare losses for low-income and rural households, which face the greatest welfare losses from the carbon tax.

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Income-based or Place-based?
Carbon Dividends under Spatial Distribution of Automobile Demand

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Abstract: We empirically examine the distributional consequences of income-based versus place-based recycling of carbon tax revenues when automobile demand varies substantially over geographic space. Using a large household dataset from Japan, we estimate a discrete-continuous choice model that parsimoniously accounts for the geographic distribution of incomes, public transit, and portfolio preferences. The model outperforms a naive random-coefficient model in explaining the observed spatial distribution of automobile demand, and allows us to estimate the price and income elasticities that vary by income and public transit density. The estimated model is used to simulate the distributional impacts of alternative revenue recycling schemes on carbon emissions and consumer welfare. We demonstrate that place-based recycling outperforms flat or income-based recycling because it allocates more rebates to price-inelastic consumers in non-urban areas whose tax incidence and expenditure shares are high and because consumer's welfare gain outweighs the negative externality cost of carbon emissions from induced demand.

JEL Codes: H23, H31, L62, Q54, Q56

Key Words: Automobiles, carbon dividend, carbon emissions, carbon tax, discrete-continuous choice, climate justice, equity-efficiency trade-off, portfolio effect, public transportation

I. Introduction

Forty-five prominent economists signed a public statement on the Wall Street Journal on January 17, 2019. The statement essentially argues for a sufficiently high, robust, and gradually rising carbon tax with full revenue recycling via equal lump-sum rebate. This revenue recycling creates "carbon dividends" in that the majority of households, including "the most vulnerable," may benefit, beyond the increased energy bills, from equal lump-sum rebates. Well founded in economic theory, the statement has received wide support from more than 3,000 economists around the world since then. Although economists agree on the key points of the statement, an important question remains as to whether the rebates should be made equally or conditioned on some socioeconomic attributes such as incomes. There is a rise in economic studies over the last decade investigating the distributional consequence of carbon mitigation policies [e.g., Andersson and Atkinson, 2020; Beck *et al.*, 2015; Cronin *et al.*, 2019; Dorband *et al.*, 2019; Fremstad and Paul, 2019; Goulder *et al.*, 2019; Grainger and Kolstad, 2010; Maestre-Andres *et al.*, 2019; see a review of the topic by Ohlendorf *et al.*, 2021]. One of the important themes that arise from the literature is that how best to design rebates in addressing a trade-off between efficiency and equity consequences of carbon pricing matters for gaining consumers' support for carbon pricing policies (Sommer *et al.*, 2022, Douenne and Fabre, 2020, 2022; Ewald *et al*., 2022).

We empirically investigate this theme in the context of carbon emissions from road transportation. Road transportation accounts for a large share of the global CO_2 emissions today, is considered harder to decarbonize than energy sector, and is also expected to continue to grow over the next decades (IPCC, 2023). Economists have long known the difficulties associated with reducing carbon emissions from road transportation [see Anderson *et al.* (2011) or Knittel (2012) for a review of the issues]. In the U.S., for example, vehicle miles travelled nearly doubled from 1970 to 2009 while the fleet average fuel economy (of only new cars) improved only at a moderate rate over the same period (Knittel, 2012). Associated with this increase in vehicle miles is the rapid urban sprawl: i.e., urban development in geographically sparse, low-density areas (Glaeser and Kahn, 2010). The form of cities, roads, and public transit networks we observe today is the result of this development, so is the demand for vehicle transport [e.g., Beaudoin and Lawell (2018); Bento *et al.* (2005); Boarnet and Crane (2001); Duranton and Turner (2011)]. As a result of such urban/rural landscape, automobile demand today is highly spatially heterogeneous: i.e., demand elasticities differ between urban, suburban, and rural contexts. We observe such spatial heterogeneity in automobile demand not only in the U.S., but in virtually all countries around the world.

Our goal in this manuscript is to empirically demonstrate the importance of this spatial heterogeneity for efficiency-equity tradeoffs in designing a carbon tax-and-dividend policy. A conventional wisdom suggests that the deadweight loss from a carbon tax would be smaller when it is levied on price-inelastic consumers, yet a larger economic burden would fall onto such consumers. This wisdom is often applied in the design of the carbon dividend policy—because low-income consumers' demand is generally price-elastic than high-income consumers' demand, equal lump-sum rebates (or income-based rebates) should, in principle, benefit low-income consumers more than high-income consumers, in net of energy bills, without compromising the economic efficiency. This logic may fail, however, in the presence of spatially heterogenous automobile demand that is more closely tied to consumers' places of living and public transit availability than their incomes. For example, demand for vehicle ownership and utilization may be highly elastic in urban areas where a dense public transit network is available, despite that their incomes are high (even after adjusting for the cost of living) because abundant employment opportunities exist. On the other hand, even a moderate carbon tax may hurt consumers living in non-urban areas not only because they may have no other means to travel (hence, their automobile demand is quite inelastic) but also because transportation costs represent a larger share of their incomes. It is empirically unclear how one should design carbon revenue rebates in the presence of such joint distributions of incomes, public transit networks, and preference structures over geographic space.

With this general theme in mind, we first estimate a spatially explicit model of automobile demand in the discrete-continuous choice framework à la Dubin and McFadden (1984), using spatially rich survey data in Japan. We then use the estimated model to simulate and characterize the distributional consequences of alternative lump-sum rebate schemes under a moderate carbon tax (\$50 per ton of CO_2 emissions).

As in Train (1993), our model accounts for a sequence of three choices: the number of vehicles owned, the class/type of each vehicle owned, and the vehicle kilometers traveled (VKT) for each vehicle owned. What is new here is that we incorporate three new aspects into the model and do so in a manner that is theoretically consistent with both the theory of travel demand (Domencich and McFadden, 1975) and the error-component formulation of mixed logit (Brownstone and Train, 1998). First, we introduce portfolio considerations in a manner analogous to Gentzkow (2007) and Wakamori (2015). That is, we explicitly model 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. Adding the portfolio effect allows us to model intricate behavioral responses that seem quite important in our empirical context, which we shall turn to below. Second, following the spirit of random-coefficient logit, we allow the parameters on (indirect) utility to depend explicitly on a measure of public transit density. This formulation generates realistic substitution patterns that are explicitly linked to public transit. For example, a consumer who has a high valuation of fuel economy because her access to public transit is limited is allowed to substitute to a less expensive alternative, such as a keicar, that has less but similar fuel economy when the price a hybrid car is too high. Third, the resulting model produces the high dimensional sample correction terms that enter the vehicle utilization equation. To address it, we employ Dahl's control function approach (2002). By this, we account for two types of correlation in the VKT equation due to unobservables: one between the uses of multiple cars and the other between car ownership and utilization. We estimate this model, using a large, nation-wide internet survey we conducted in 2016. The survey contains a usable sample of approximately 100,000 households, and hence, we have a sufficiently large subsample within each decile of public transit density.

The covariates' variations that come with it allows us to estimate the demand parameters that vary by that density. As with all analogous studies using household survey data [e.g., Bento *et al.* (2005), Bento *et al.* (2009), Goldberg (1998), Train (1986), West (2004)], the identification and estimation of the model parameters is challenging. We discuss our empirical strategy in depth in Section V.

The estimated model produces two key results that are important for our counterfactual policy simulations. First, our model outperforms the standard random-coefficient logit in predicting the ownership shares of different car portfolios over geographic space relative by a large margin. In particular, the model predicts not only the overall car ownership shares but also the ownership shares of *keicars* (extremely compact cars with displacement capacity of 660 cc or less), which account for 40-50% of owned cares in non-urban areas. Second, we estimate the price and income elasticities of vehicle ownership and carbon emissions by income as well as by transit density quintiles and show that these elasticities are indeed highly spatially heterogeneous and are imperfectly correlated with incomes. We find that the estimated price and income elasticities of car ownership decrease with household income levels (holding public transit density) and increase with public transit density (holding household incomes). The elasticities of CO_2 emissions (incorporating car utilization), however, do not monotonically increase or decrease with public transit density (holding household incomes). This makes it empirically quite ambiguous which scheme performs better than others.

Next, the estimated model is used to simulate the distributional consequences of three lump-sum rebate schemes under the carbon tax of $50 per ton of CO_2 emissions: (a) no rebate, (b) flat (or uniform) rebates, (c) income-based rebates, and (d) place-based rebates (Section VII). For all schemes, we apply full revenue recycling: all revenues are rebated back to consumers in a lump sum manner. We evaluate not only the impacts of these alternative policy scenarios on the overall carbon emissions and the consumer welfare, but also their spatial distributions over geographic space. To assess the impact on consumer welfare, we estimate the compensating variation using Herriges and Kling's (1999) approximation to the Small and Rosen's (1981) formula. We note, however, that our attempt is to empirically demonstrate the importance of spatial demand heterogeneity for economic evaluation, not to simulate all realistic equilibrium responses to these policies, which is infeasible in our study because we lack data that would allow us to estimate spatially-explicit supply-side parameters. For each scenario, therefore, we simulate only the demand-side responses, assuming perfectly elastic supply.

Our counterfactual simulations demonstrate three important findings. First, regardless of the rebate schemes, the rebates to consumers mitigate some of the welfare losses from the carbon tax while its perverse impact on carbon emissions from increased driving demand are negligibly small. This result supports economists' views in favor of a carbon dividend. Second, the welfare-enhancing effect of rebates are not large enough to offset the welfare loss from the carbon tax. This result is driven by the inelastic automobile demand particularly in non-urban areas. Third, the place-based rebate scheme outperforms all other schemes (no rebate, the flat rebate, and the income-based rebate schemes) in terms of aggregate social welfare. The place-based scheme allocates more rebates to consumers in areas with low public transit density subject to the government revenue neutrality constraint. These non-urban consumers have more price-inelastic demand for vehicle transport and spend a larger share of their incomes than those in urban areas. Hence, allocating more rebates to the non-urban consumers has a larger compensating effect, in terms of mitigating the welfare loss and the regressivity of the carbon tax. Although the place-based rebates induce more demand from non-urban areas, this effect is quite small. As a result, the overall social welfare is higher under the place-based scheme than any other schemes. We also consider two additional scenarios: (e) more aggressive place-based rebates and (f) a higher carbon tax of $200 per ton. The results are even more supportive of our general argument—place-based rebates are generally more welfare-increasing and emissions-decreasing than flat or income-based rebates. We believe that these results provide important insights for economists and policy practitioners who are interested in better social acceptance of carbon pricing and climate justice.

Our work complements several strands of literature: (a) empirical studies that estimate the discrete-continuous decision model on car ownership and utilization, with applications to the effect of gasoline tax [Bento *et al.* (2009), Train (1986), and West (2004)], to the effect of CAFÉ standards [Goldberg (1998)], and to the effect of feebates [D'Haultfoeuille *et al.* (2014)] and empirical studies that investigate (b) the relationship between urban structures and demand for vehicle transport, either using city-level observations [e.g., Levinson and Kumar (1997); Glasear and Kahn (2010)] or household-level observations [e.g., Beaudoin and Lawell (2018); Bento *et al.* (2005); Boarnet and Crane (2001); Train (1986); Gillingham (2014); Gillingham *et al.* (2015)], (c) the economic incentives for efficiently controlling emissions from mobile sources [see Knittel (2012) and Anderson *et al.* (2011) for a comprehensive review on the topic], and (d) the distributional consequences of carbon mitigation policies [e.g., Andersson and Atkinson, 2020; Beck *et al.*, 2015; Cronin *et al.*, 2019; Dorband *et al.*, 2019; Fremstad and Paul, 2019; Goulder *et al.*, 2019; Grainger and Kolstad, 2010; Maestre-Andres *et al.*, 2019]. In addition, our paper has an important implication to the literature investigating the factors that affect political support for carbon pricing [Sommer et al., 2022, Douenne and Fabre, 2020, 2021; Ewald *et al.*, 2022]. Our results indicate that consumers who need to rely on cars for daily transportation may prefer place-based rebates than flat or income-based rebates. Our findings are consistent with recent studies which find that car owners are less likely to support carbon pricing (Dechezleprêtre *et al.*, 2022) and the perceived effect of carbon taxes on fuel prices is often the key driver to consumer acceptance of carbon pricing (Douenne and Fabre, 2020; 2022).

II. Background and Motivation

II-1. Empirical Background

We start by presenting a statistical overview of the relationship between access to public transit and vehicle-related household choice in Japan in Figure 1. In the figure, we plot (a) the share of households who own at least one car, and conditional on having at least one car, (b) the share of keicars and (c) the share of hybrid cars, against the deciles of public transit availability, for each income quartile. The figure also plots (d) the share of households owning keicars and another vehicle type among those holding two or more cars. For ease of interpretation, these ownership shares are reported against a single composite index of public transit density.[2]

Several important observations emerge from the figure. First, the car ownership rate sharply declines with public transit density for each income group and the ownership-income gradient appears smaller compared to the gradient with respect to public transit density, although the car ownership rate also declines with household income for each public transit density level. Second, conditional on owning at least one car, the households in low transit density areas have a substantially higher likelihood of owning *keicars*, despite that roads are typically much wider in rural areas than in urban areas. This seems in sharp contrast to U.S. and other parts of the world where we tend to observe a higher prevalence of large pickup trucks in low-density areas. Although this tendency holds for each income quartile, the share of *keicars* is much higher for low-income groups than high-income groups, implying that the income variation is important in accounting for the types of cars held. Third, we observe that the demand for hybrid cars is virtually invariant with respect to the public transit density. This is somewhat puzzling because the demand for vehicle transport increases quite sharply, so does the demand for fuel economy, as public transit becomes more sparsely available. Hence, we would expect the demand for *both* hybrid cars and keicars to increase with a decline in public transit availability, holding household income. Fourth, conditional on owning two or more cars, the households in low-density areas have a higher likelihood of owning cars of *different types* than in high density areas. This tendency is particularly prevalent for high-income households.[3]

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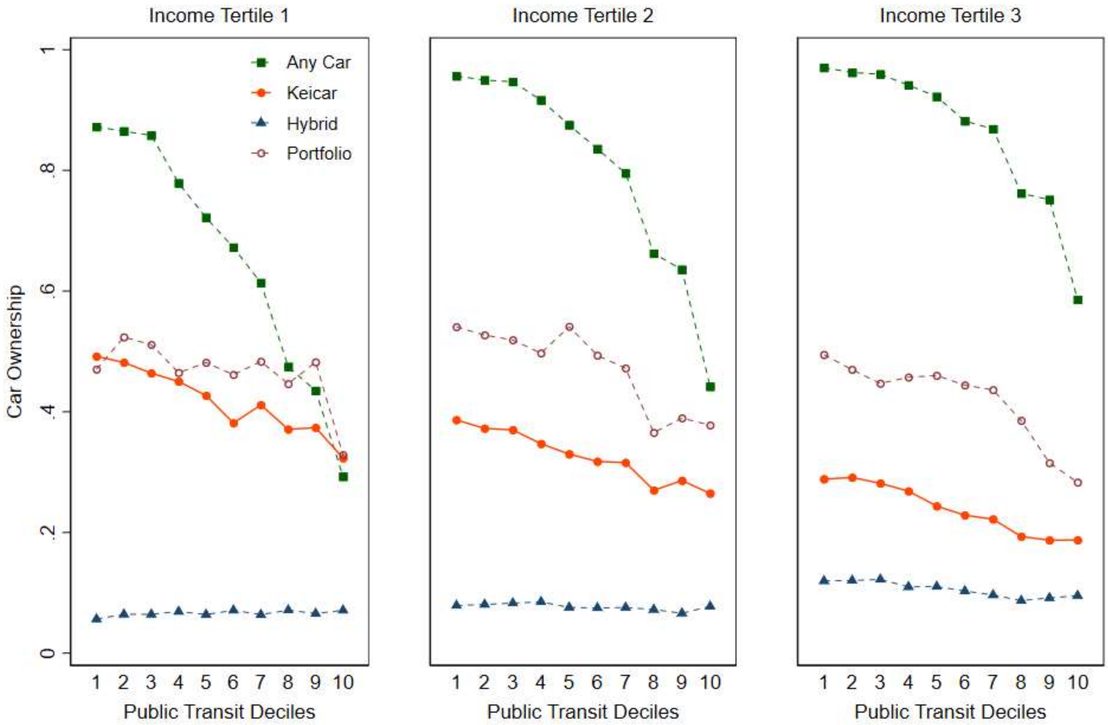
[2] We construct this index by an (unweighted) average of two district-level measures of railway transit network (incl. cable cars, surface rails, and subways). The first measure is the kilometers of railways per square kilometer and is intended to measure ease of access to destinations via railways. The second is the percentage of the habitable area within a district that has at least one train station within 15-min walking distance and is intended to measure ease of access to railways. We do not include the bus network in this index because in Japan, bus network is highly developed and even rural residents have access to a bus station within a walking distance. Figure B.1 in the appendix demonstrates that the composite index using railways has an increasing, but non-linear relationship to population density while the index using buses has very little geographic variation.

[3] In our data, only 6% of households in our data own three or more cars and of those who own two (or more) cars, only 36% own the same type of vehicles. The remaining 64% own a combination of either regular-keicar (24.5%), regular-minivan (16.3%) or keicar-minivan (23.2%).

Figure 1. Type and Level of Car Ownership
by Income and Public Transit Density



Note: The figure plots the household shares representing different types of car ownership against deciles of public transit density for each income quartile. Green lines with squares represent the share of households who own any car. Red lines with circles and blue lines with triangles represent, respectively, the shares owning *keicars* and hybrid cars among households who own any car. Maroon lines with hollows show the shares owning *keicars* with another type of cars (minivan or sedan) among those who own two or more cars. The data come from the household survey in 2015, the details of which are explained in Section IV.

These observations not only motivate our econometric modelling strategy but also substantiate the importance of our research question: Should we design carbon revenue recycling based on income, place of living, or both? The figure demonstrates that the demand for cars as well as for fuel economy and different varieties of cars varies substantially over geographic space, even after controlling for incomes. And this geographic variation is clearly related to public transit availability. This is an example of a classic trade-off in designing an optimal tax revenue recycling scheme: We would like to tax on commodities (or consumers) whose demand is inelastic (for efficiency), but may also need to compensate them because such commodities may serve the basic needs of the consumers (for equity). In our case, the automobile demand in low-density areas may be highly inelastic, regardless of household incomes, because there may be no viable substitute for cars in meeting daily transportation demand.[4]

[4] Konishi and Zhao (2017) find that in Japan, the price elasticities of automobile demand are smaller for small-sized vehicles than for large-sized vehicles, despite that low-income households tend to buy smaller cars, and hence, the demand for these cars is expected to be price-elastic, in principle.

II-2. A Simple Motivating Model of Carbon Revenue Recycling

This section lays out a simplified model of carbon revenue recycling to motivate our empirical investigation. Consider an economy consisting of a continuum of consumers who make a consumption decisions on a composite good c (which serves as a numeraire) and a transport good v (modelled as an abstract one-dimensional composite representing both ownership and utilization of vehicles). Assume consumers have inelastic labor supply so that their incomes y_i are given exogenously. Let $\tilde{u}_i$ be consumer i's indirect utility and $\tilde{v}_i$ be the (Marshallian) demand for the transport good given her income and the tax-inclusive good price $p(t)$. Let τ be the (constant) negative external cost per unit of the transport good. Assume that the government sets the gasoline tax at the efficient level, $t = \tau$. In the absence of revenue recycling, such a tax will maximize the social welfare given by:

$$W = \int \tilde{u}_i(y_i, p(\tau))di - \tau \int \tilde{v}_i(y_i, p(\tau))di$$

Now consider the lump-sum rebates T_i subject to the revenue neutrality constraint $\int T_i di = \tau \int \tilde{v}_i(y_i, p(\tau))di$. Such a transfer generally has two kinds of impacts: the increase in indirect utility and the increase in negative externality due to an associated increase in transport demand. Letting $\omega_i \equiv \partial\tilde{v}_i/\partial y_i$ be the income elasticity of transport demand, with $\Delta y_i \approx T_i$, we can write the corresponding change in social welfare (relative to no rebate) as:

$$\Delta W = \int \{u_{c,i} + \omega_i(u_{v,i} - p(\tau)u_{c,i} - \tau)\}\Delta y_i\, di$$

where $u_{c,i} = \partial u_i/\partial c_i$ and $u_{v,i} = \partial u_i/\partial v_i$. By the private optimality condition for consumers, the first two terms in the parenthesis in the integral must sum to zero: $u_{v,i} - p(\tau)u_{c,i} = 0$. Hence, the above expression can be simplified to:

$$\Delta W = \int \{u_{c,i} - \tau\omega_i\}\Delta y_i\, di.$$

We now see the essence of our research question. A conventional rebate scheme focuses on the impact on the first term in the integral. The social welfare would be higher if more rebates are made to low-income consumers whose marginal consumption utility is generally higher, all else equal. However, there is another term in the parenthesis, which captures the perverse effect of revenue recycling. The vehicle emissions might be higher if more rebates are made to consumers whose income elasticity of transport demand is higher. Moreover, holding the income level, the marginal consumption utility would be generally higher for consumers who spend a larger share of their incomes on driving. The reasoning suggests that it is empirically quite ambiguous whether a place-based rebate scheme is more welfare-increasing than an income-based scheme. To evaluate this question, we estimate a spatially explicit empirical model of automobile demand, which we turn to in the next section.

III. The Econometric Model

Our goal in this section is to lay out the econometric model of demand for vehicle ownership and utilization that is allowed to vary by geographic space, with a parsimonious set of estimable parameters, accounting for the joint distribution of income, public transit, and portfolio preferences over geographic space. To do so, we build upon a large literature in transportation research that empirically examines consumer's vehicle ownership and utilization in the spirit of the continuous-discrete choice framework following Dubin and McFadden (1984). In that literature, consumer's choice is modeled as a two-stage decision process. In the first stage, the consumer chooses whether to own a car or not, and if she does, which type of car to own. In the second stage, the consumer chooses how much to drive over a given period of time. Our empirical framework follows this tradition, but extends it in several important ways.

Vehicle Ownership: Consumers make a trade-off between money spent on buying a car versus the utility of owning and driving that car, as in the conventional literature [e.g., Bento *et al.* (2009), Berry *et al.* (1995, 1999), Goldberg (1998), West (2004)].[5] Thus, consumer i's (indirect) utility from ownership of vehicle portfolio j in location s consists of two economic components, the expected utility from net income and the expected utility from vehicle ownership and utilization:

$$u_{ijs} = \rho \ln(y_i - r_{ij}) + v_{ijs}(X_i, Z_j, S_{is}) + \epsilon_{ijs}, \tag{1}$$

where y_i is i's household income, r_{ij} is the annual rental price of vehicle ownership for car j for household i, and v_{ijs} is consumer i's expected utility from owning alternative j, and ϵ_{ijs} is a pure stochastic error term distributed independently and identically across households, alternatives, and locations. v_{ijs} is a component that captures correlation across choices and heterogeneity across households due to household-specific attributes X_i, choice-specific attributes Z_j, or location-specific factors S_{is}, some of which may be unobservable (stochastic).[6] Note that although the parameter on net income ρ is not allowed to vary by household, the income and price elasticities of demand still differ

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[5] In this paper, the unit of observation is a household, but we use the term "consumer" and "household" interchangeably, assuming that the consumer responding to the household survey represents the household's decision.

[6] In the earlier draft, we estimate the model with and without the random coefficients, but we only present the model without the random coefficients in this manuscript since the results are largely similar.

across households and depend on X_i, Z_j, and S_{is}, in general, because the consumer demand is a non-linear function of observables.

Let $j = 0$ be an "outside option": i.e., not owning any vehicle. Naturally, consumers who choose this option would use public transportation for daily transport mode. Because this "index of desirability" v_{i0s} summarizes the maximal utility from sub-trip decisions conditional on owning no car (Domencich and McFadden, 1975), v_{i0s} (not u_{i0s}) should, in principle, depend on the quality of public transportation (which is a component of S_{is}). Given the additive separability we assume in (2.1), we re-define the second term as the *utility difference* relative to the no-car option, $\psi_{ijs} \equiv v_{ijs} - v_{i0s}$, so the term now includes the value of public transportation. This utility component ψ_{ijs} is assumed to have the following linear-in-parameter structure:

$$\psi_{ijs} = \delta_{is}' Z_j = (\delta_0 + \delta_1' X_i + \delta_2' S_{is}) Z_j.$$

This specification conforms to a natural economic intuition that the marginal utility of a vehicle attribute varies by household as well as geographic characteristics.[7] Because we include a rich set of covariates in X_i and S_{is}, our model can flexibly capture sufficiently rich covariance structures of the error components, $E\left[\xi_{ijs}' \xi_{ijs}\right]$, underlying true substitution patterns. In our empirical implementation, we use the public transit density as one of the key variables in S_{is} so that the consumer's utility of driving depends on the access to public transit. It is worth emphasizing, however, that this should not be mistakenly interpreted as if we are estimating the causal effect of public transit availability—we are not. Rather, this should be taken as estimating the heterogeneous effects of the rental price and other car attributes on car choices, assuming that household-level or district-level characteristics (incl. public transit density) are pre-determined prior to the vehicle ownership decision.

Portfolio Effect: Our discussion in Section II substantiates the importance of accounting for preferences for particular vehicle portfolios that may vary over geographic space. Hence, we augment the above model by allowing for the dependence of choices across multiple vehicle holdings. We follow Gentzkow (2007) and Wakamori (2015) and define consumer i's utility from owning a pair of cars j and k as follows:[8]

[7] Note that we can re-write this equation so it is expressed as the error-component formulation:

$$\delta_{is}' Z_j = (\delta_0 + \delta_1' X_i) Z_j + \delta_2' S_{is} Z_j = \phi_{ij}(X_i, Z_j) + \xi_{ijs}(S_{is}, Z_j).$$

Thus, our econometric model is amenable to the error-component interpretation: the ownership value of a particular alternative j to a consumer depends on the consumer's underlying preferences for certain types of vehicles. Such consumer preferences depend naturally on household-specific and location-specific factors because the ownership value, by definition, incorporates the value of sub-trips the consumer would make when she owns the car relative to the case of having no car (Domencich and McFadden, 1975). As discussed in Brownstone and Train (1998) and McFadden and Train (2000), this error-component structure can generate flexible substitution patterns (e.g., any type of nested logit as a special case), allowing us to alleviate the "independence from irrelevant alternatives (IIA)" property. This is true even when we include only observables in S_{is}.

[8] We restrict consumer's choices to a maximum of two vehicles per household since we have detailed information only on

$$u_{i(j,k)s} = \rho \ln\left(y_i - r_{ij} - r_{ik}\right) + \psi_{ijs} + \psi_{iks} + \Gamma(j,k;X_i,S_{is}) + \epsilon_{i(j,k)s}, \tag{2}$$

where $\Gamma(j,k;X_i,S_{is})$ is the portfolio-effect term, which captures the idea that households derive utility from owning a particular combination of vehicle types. For example, households with children may prefer owning a minivan for recreational use, yet may prefer owning a sedan or keicar for daily commuting use. As in Wakamori (2015), we consider three mutually exclusive sets of vehicle types: i.e., keicars $\mathcal{K}$, sedan/regular cars $\mathcal{R}$, and minivans $\mathcal{M}$. Then the portfolio effect is given by

$$\Gamma(j,k;X_i,S_{is}) = \kappa'_{(j,k)} x_{is},$$

where x_{is} denotes a vector of characteristics of household i in residence s (incl. constant) and $\kappa_{(j,k)}$ is the combination-specific parameter for a pair (j,k).

There are several advantages of modeling the portfolio considerations this way. First, as discussed in Wakamori (2015), the approach does not assume products are either complements, substitutes, or independent, and instead, allow the estimates of parameters to flexibly capture complementarity patterns observed in the data. Second, we can estimate this model using conventional conditional logit routines available in most statistical packages. Lastly, this formulation exploits an important property of mixed logit: an analog to nested logit of any complexity can be obtained by adding interaction terms with a set of dummies representing the nests (Brownstone and Train, 1998). In eq. (2), we use a set of dummies, each representing a particular portfolio, and then, interacting each of these dummies with household-level or geographic-level observables. The former essentially works the same as having a nest for each vehicle portfolio while the latter works as allowing the correlation across choices within the nest to depend on observables.

Vehicle Utilization: The conventional approach to estimating the demand for driving distance is to apply Roy's identity to the indirect utility and derive the driving distance equation that is theoretically consistent [e.g., Bento *et al.* (2005), Bento *et al.* (2009), Goldberg (1998), West (2004)]. We follow this tradition and apply the following empirical approximation to the Roy's identity.[9] That is, we assume that monthly driving distance m (in log) for vehicle j of consumer i who lives in area s and who also owns vehicle k is:

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two most frequently used cars. In our sample, only 6% of the households in our data hold three or more cars.

[9] Note that applying Roy's identify to eq. (2), we obtain:

$$\ln\left(m_{ijs|k}\right) = \ln\left(-\frac{\partial u_i/\partial p_j}{\partial u_i/\partial y_i}\right) = -\ln(\rho) + \ln\left(y_i - r_{ij} - r_{ik}\right) - \ln\left(p_j\right) + \ln\left(-\frac{\partial v_{ijs}}{\partial \ln p_j}\right).$$

Thus, our empirical specification can be thought of as simply allowing for the flexible parameter estimates for each term while imposing the theoretical consistency between equations eq. (2) and (3) via Roy's identity.

$$\ln m_{ijs|k} = \alpha_{is} \ln(y_i - r_{ij} - r_{ik}) + \beta_s \ln p_{ij} + \lambda' W_{ijs} + \eta_{ijs}, \tag{3}$$

where y_i and r_{ij} are as defined above, p_{ij} is the operating cost of utilization per unit of driving distance for car j for household i, W_{ijs} is a vector of household, vehicle, and geographic characteristics, and η_{ijs} is the error term. The primary parameters of interest are the income and price elasticities, α_s and β_s, of vehicle utilization. We allow these parameters to depend on the geographic characteristics S_{is}: $\alpha_s = \alpha + \gamma'_\alpha S_{is}$; $\beta_s = \beta + \gamma'_\beta S_{is}$. In contrast to eq. (1), without explicitly allowing for interaction terms, the income/price elasticity will be constant across areas.

Selection Correction: It is known that OLS regression of eq. (3) would generally give us biased estimates of parameters due to sample selection because we observe each consumer's driving behavior only for the car model chosen, but not for car models that had not been chosen.[10]

To address this selection problem, previous studies either assumed a joint distribution of errors in the two equations of ownership and VKT or used a selectivity correction a la Dubin and McFadden (1984). The former is known to place severe restrictions on the selection process, while the latter is known to become imprecise or infeasible when there are many alternatives in the first stage decision. We instead use Dahl's (2002) control function approach to correct for this selection bias in the case of many alternatives. Specifically, Dahl showed that, in case of high-dimensional alternatives, eq. (3) can be consistently estimated using estimates of individual purchase probabilities:

$$\ln m_{ijs} = \alpha_s \ln(y_i - r_{ij}) + \beta_s \ln p_{ij} + \lambda' W_{ijs} + \sum_{j=1}^{J} M_{ij} \times T_{ij}(P_{i0}, P_{i1}, \dots, P_{iJ}) + v_{ijs} \tag{4}$$

where $T_{ij}(\cdot)$ is some unknown function of purchase probabilities $P_{i1}, \dots, P_{iJ}$ and M_{ij} is its parameters. Dahl suggests that, in practice, we may include only a few probabilities such as the probabilities of the first-best choice, the second-best choice, and the outside option. We follow this advice in our estimation.

There is one subtle, yet important, issue in estimating the VKT regression eq. (4). We observe VKT for each of the vehicles owned, and hence, eq. (4) must be estimated separately for each vehicle, accounting for that vehicle's attributes. Here, the difficulty is that the households who own multiple cars are likely to decide on how often to use one vehicle jointly with other vehicles. Consequently, the utilization levels are likely to be correlated across car holdings. The literature to date seems silent as to how to address this issue. In her seminal work, Goldberg (1998) estimates the VKT regression using observations on newly purchased

[10] See Online Appendix A for more details.

cars only, ignoring this correlation in vehicle utilization. Bento *et al.* (2005) instead use the VKT per vehicle, averaged over vehicles owned, as a dependent variable, excluding vehicle-specific regressors from the list of independent variables.

In the context of the present paper, the policy impact on the second car's VKT is quite important. Hence, we address this issue as follows. We estimate the VKT regression, pooling all VKT observations on the two most frequently used cars, with a dummy indicating a second car. This ensures that the same sample correction terms enter the VKT regression for the two cars owned by the same household, yet accounting for the fact that one of the observations is on the second car. This allows multiple-car owners' vehicle utilization decisions to be correlated across their vehicle holdings, either through observable household-level characteristics or through (unobservable) selectivity terms. Because our model of car ownership accounts for portfolio effects, the selectivity correction terms in eq. (4) control for the unobservable correlations that are specific to the same household who decide to own a particular combination of cars.[11]

No Cross-equation Restriction for Estimation/Identification: Our empirical model described in eq. (1)–(3) is theoretically consistent in that there exists an underlying economic model that conforms to Roy's identity. We, however, do not impose the cross-equation restriction on the parameters of the model using Roy's identity. Instead, we flexibly estimate the parameters of the model and use Dahl's control function approach to correct for the selection bias. We take this approach because we place a greater emphasis on the empirical account of spatially explicit automobile demand that is also amenable to economic interpretation rather than binding the parameters by a priori model structures. In the earlier literature, researchers often impose ad hoc assumptions on the form of indirect utility to arrive at a convenient form of estimating equation for driving distance a la Roy's identify. This, however, often results in specifications that are difficult to justify empirically. For example, Bento *et al.* (2009), by far the state-of-the-art, most sophisticated empirical research on the topic to date, estimate the discrete-choice model of car ownership jointly with the continuous driving distance equation, directly imposing Roy's identify in the estimation. A similar approach is taken in Jacobsen (2013). Although their approach has important advantages, namely efficiency and theoretical consistency of parameter estimates, it also results in an unfortunate a priori restriction that the marginal utility parameter on the valuation of fuel economy in the discrete choice of vehicles is the same as the parameter on the price elasticity of driving distance. Although this identity must hold in economic theory, it needs not be empirically, given the findings from the large empirical literature on consumer myopia [e.g., Busse *et al.* (2013), Allcott and Wozny (2014), Grigolon *et al.* (2018), Leard *et al.* (2023)]. Indeed, in our companion paper, we use Mote Carlo simulations to demonstrate that in the

[11] One could, instead, estimate the seemingly unrelated regression or the second-car's VKT equation independently. Both approaches resulted in parameter estimates that are hard to interpret. For example, the estimated elasticity on net income was negative. We would think that this occurs precisely because of the substitution in vehicle utilization between the two cars. The households with high incomes primarily drive the first car for daily use, keeping the second car only for luxurious use. The households with low incomes, on the other hand, are likely to own the second car for primary use, and hence, they drive the second car more. The estimates may be simply capturing this correlation.

presence of consumer myopia, the cross-equation restrictions using Roy's identity generally result in substantial bias in parameter estimates whereas estimation without the restrictions leads to estimates that are far closer to true parameters.[12]

IV. Data

Our study relies on a large cross-sectional sample of households from a nationwide internet survey conducted in November 2016 in Japan. In designing the survey, we aimed for two goals. The first is to obtain a sufficiently large sample, with variations in household-level characteristics, for each population density decile. This is essential for our study because we need comparable households to separately identify the demand parameters that vary by income and public transit: i.e., those with different levels of income, yet with the same level of access to public transit as well as those with the same level of income, yet with different levels of access to public transit. The second is to collect sufficiently detailed information on each household's vehicle ownership and utilization that is comparable to the U.S. Consumer Expenditure Survey (CES). In particular, we aim to collect information such as the number of vehicles, the vehicle type (fuel economy, engine/fuel type, horsepower, make, size, weight, vintage), the year/month of purchase, and the vehicle kilometers traveled since the purchase. Such detailed information on vehicle ownership and utilization is not available in national consumer surveys in Japan.

The survey was administered under the contract with Nikkei Research Inc. to the pool of registered internet monitors. The survey resulted in a sample of 105,000 usable respondents with complete responses. As with other internet-based surveys, we did not have direct control over the sampling process. Our usable sample, however, covers a sufficiently large number of households in every prefecture, with sufficient variation in key socioeconomic variables such as age and income. The geographic distribution of our survey respondents by prefecture is sufficiently close to the population distribution, though populated prefectures (e.g., Tokyo and Kanagawa) are over-represented while less populated prefectures (e.g., prefectures in Kyushu region) are under-represented. As expected, average household incomes in our sample are slightly higher than in the population for most prefectures, although we do not see significant differences in average household sizes. Our results may be somewhat biased toward households with relatively higher incomes.[13]

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[12] In addition, Dube *et al.* (2022) also show that the discrete-continuous model of consumer demand is generally not integrable in the Hurwitz-Uzawa sense when the continuous demand is not perfectly inelastic—the case we and all previous studies on automobile demand consider. Thus, it may be simply infeasible to construct a model that satisfies all theoretically desirable properties that is also empirically defensible. However, as discussed in Hanemann (1984), any discrete-continuous choice model of consumer demand generally leads to switching regression models of the form we discuss above. In this sense, our approach closely follows the well-grounded theory of the discrete-continuous model, and thus, should be taken as a good compromise between the desire for empirical validity and that for theoretical consistency.

[13] There is a large literature in environmental economics, examining the extent of bias in demand estimation that may arise due to the internet-based survey. The results are mixed. Comparing the internet survey versus other modes of survey, some (Lindhjem and Navrud, 2011 and Nielsen, 2011) report no or small bias while others (Boyle *et al.*, 2016) report a non-negligible bias.

We supplement the survey with the data from various sources. First, we use the GIS datasets on city boundaries, bus stops, train stations, train networks, hospitals, road length, and public parks from the National Land Numerical Information Download Service, made available online by the Ministry of Land, Infrastructure, and Transportation (MLIT). We use the coordinates of train stations and the line data on train networks to construct the composite measure of public transit density at the 'city-district' level (see Section II-1). Our definition of 'city-district' follows that of the Ministry of Internal Affairs and Communications. As of 2018, there are 1,724 city districts in Japan. Second, we also use the car catalog data from the carsensor.net, one of the largest online car retailers in Japan. The survey respondents are asked to provide detailed information on each of the cars they own (up to their second car): i.e., model year/month, purchase year/month, make, model name, displacement level, curb weight, and mileage. We use these to match their cars with those listed in the carsensor.net catalog to obtain other vehicle characteristics such as fuel economy ratings, horsepower, size, and transmission. Third, we use the district-level population estimates provided by the National Institute of Population and Social Security Research. Lastly, we also obtain a measure of prefecture-level road congestion from MLIT, regional consumer price and gasoline price series from the Ministry of Economy, Trade and Industry, historical discount rates from the Bank of Japan, and district-level garage certification regulations from Keicar Information Center. Detailed descriptions on how we define our choice set (for vehicle ownership) and key variables used in the manuscript are available in the Online Appendix B.

Table 1 reports the means and standard deviations of key variables by population density. The table confirms substantial variations both within and across population density quintiles, which we exploit in our estimation. First, all measures of public transit sharply decrease as population density declines. Not only that, we have substantial variation in these measures within each density quintile, and interestingly, more so in low-density quintiles: coefficients of variation are 0.57, 0.45, 0.45, 0.28, and 0.21 for the lowest, 4th, 3rd, 2nd and the highest population densities. This is in sharp contrast to household characteristics. Average household incomes decline as population density declines, yet the coefficients of variation stay roughly the same across all quintiles. The same is true with household size. This 'within' variation in public transit measures helps us identify the effects of public transit on vehicle ownership/utilization. Second, as we have seen, the rate of car ownership rises quickly as population density declines, possibly in response to declines in public transit availability. Interestingly, however, the coefficient of variation for car ownership declines as population density declines. Instead, the coefficient of variation for the number of cars owned rises, from 0.33 in the highest density quintile to 0.52 in the lowest density quintile. This point is also closely related to our next observation. Third, we observe a smaller variation in vehicle utilization than vehicle ownership: after taking logs, the coefficients of variation for monthly VKT range from 0.17 to 0.19 for the first car (= most frequently used car), and from 0.18 to 0.24 for the second most used car. Combined, these two observations are suggestive of the tendency that households absorb the impact of public transit (un)availability by adjusting the number of cars owned rather than by adjusting the vehicle utilization. We

Table 1. Descriptive Statistics by Population Density Quintiles

	Population Density Quintiles									
	Lowest		4th		3rd		2nd		Highest	
Number of obs. (households)	20,963		20,851		21,041		21,078		21,033	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Public transit density	0.112	0.064	0.178	0.080	0.277	0.125	0.392	0.110	0.559	0.119
Congestion measure	0.595	0.108	0.689	0.105	0.753	0.136	0.813	0.103	0.899	0.062
Household income (10,000 yen)	601.6	410.1	634.6	427.1	656.1	442.5	684.1	460.7	746.1	530.1
Household size [Num. of people in household]	2.94	1.39	2.88	1.32	2.81	1.27	2.70	1.24	2.52	1.25
Own car? [1 = yes]	0.938	0.241	0.908	0.289	0.829	0.376	0.730	0.444	0.497	0.500
Drive to work? [1 = yes]	0.548	0.498	0.434	0.496	0.266	0.442	0.154	0.361	0.070	0.256
Num. of cars owned [of those who own car]	1.73	0.90	1.56	0.78	1.32	0.61	1.17	0.44	1.09	0.36
Most frequently used car										
Monthly VKT	1,162.7	2,378.0	1,000.6	1,916.8	892.3	1,884.1	785.6	1,837.6	730.3	1,785.4
Price (10,000 yen)	199.6	129.3	206.5	135.4	218.9	140.0	229.7	150.7	261.7	182.1
Fuel economy (km/L)	20.4	7.6	20.5	7.7	19.8	7.6	19.3	7.7	18.5	7.7
Vehicle size (mm) [length + width + height]	7,276.2	819.0	7,297.1	801.1	7,394.9	783.4	7,457.4	793.8	7,537.6	844.1
Hybrid [1 = yes]	0.135	0.342	0.146	0.353	0.146	0.353	0.150	0.357	0.150	0.357
Keicar [1 = yes]	0.349	0.477	0.327	0.469	0.289	0.454	0.254	0.436	0.221	0.415
Second most used car										
Monthly VKT	964.4	1,920.3	940.7	2,231.6	937.0	2,318.8	941.9	2,856.1	1,065.5	3,399.3
Price (10,000 yen)	170.8	116.4	180.8	128.6	194.7	151.9	215.9	184.1	283.5	268.5
Fuel economy (km/L)	21.1	7.0	21.0	7.1	21.0	7.3	20.2	7.6	19.0	7.3
Vehicle size (mm) [length + width + height]	7,037.7	760.9	7,058.4	777.2	7,068.4	838.0	7,192.5	843.2	7,234.9	1,050.5
Hybrid [1 = yes]	0.039	0.195	0.035	0.183	0.023	0.150	0.015	0.122	0.009	0.096
Keicar [1 = yes]	0.531	0.499	0.501	0.500	0.480	0.500	0.420	0.494	0.329	0.470
Portfolio shares [of those who own two (or more) cars]										
Keicar-Keicar	12.4%		10.8%		11.5%		10.5%		7.2%	
Keicar-Regular	26.9%		25.9%		25.4%		25.4%		21.4%	
Keicar-Minivan	32.4%		31.8%		31.7%		31.2%		29.5%	
Regular-Regular	6.8%		8.7%		9.0%		9.4%		11.9%	
Regular-Minivan	12.6%		12.9%		14.0%		13.4%		16.3%	
Minivan-Minivan	8.9%		9.9%		8.4%		10.2%		13.7%	
Total share	100.0%		100.0%		100.0%		100.0%		100.0%	

take this as suggesting that it is indeed important to account for correlation between ownership decisions and utilization decisions. Lastly, the sample characteristics of the first car seem to differ substantially from those of the second car. The second cars are cheaper, more fuel-efficient, and smaller on average in virtually all density quintiles (while coefficients of variation are similar between the first cars and the second cars). Interestingly, for their first cars, households in low-density areas are more likely to own hybrid cars than in high density areas. Yet, the opposite is true with their second cars. These points seem to re-confirm the existence of the portfolio effect discussed in Section II.

V. Estimation and Identification Strategy

The discrete-continuous choice model we develop in Section III is estimated in two steps. In the first step, we estimate the discrete choice model, assuming the form of indirect utility as in eq. (2) and the Type-I extreme value distribution for ϵ. For this step, estimation is done by Stata's alternative-specific conditional logit routine. In the second step, we estimate the VKT regression in eq. (4), pooling all VKT observations for all cars owned by households in the sample. In this step, we use polynomials of predicted probabilities from the first step as selection control terms as in Dahl (2002). We experiment with a polynomial of up to third degree, using the probabilities of the chosen, the no-car, the highest-likelihood, the second highest-likelihood, and the lowest-likelihood options. Based on the sign/significance of key variables (i.e., net income and cost per kilometer of driving) as well as their robustness to varying levels of controls, we end up using the second-degree polynomials of the highest, the second-highest, and the lowest probabilities. Furthermore, with this approach, the conventional covariance estimator is biased (Dahl, 2002). Hence, we use bootstrapped standard errors, with 500 draws, for inference.

Because we use one-shot household survey for both steps, the identification of the parameters relies on cross-sectional variation at both the household and the district levels in economic/geographic variables. Though this poses a challenge in identification, this is typical of studies that estimate the discrete-continuous choice model of car-holding decisions using survey data (see Goldberg, 1998, Bento *et al.*, 2005, and Bento *et al.*, 2009). In the literature, four identification challenges are discussed: (1) endogeneity of measures of public transit and (2) endogeneity of rental price of car ownership in the first-stage choice of car ownership; (3) endogeneity of operating cost of car utilization (due to sample selection) in the second-stage choice of car utilization; (4) the endogenous duration of car ownership. Dut to our space limitation, we discuss each of these and our strategies to address them in the Online Appendix C. The bottom line here is that we essentially treat all household and geographic characteristics as pre-determined variables, and hence, we use these as the sources of variation for identifying the (heterogenous) effects of car attributes on car ownership and utilization choices. We, however, use two additional strategies to address the endogeneity issues (1) and (2) above. The first is to apply the two-stage residual inclusion (2SRI) method of Terza *et al.* (2008) using the railroad networks as of 1980 as an instrument. The second is to use the car-related tax incentives at the time of purchase as an additional source of variation in rental prices. Both of these and other related issues are discussed in more detail in the Online Appendix C.

VI. Estimation Results

IV-1. Car Ownership and Utilization

We first report on the first-stage discrete choice model of car ownership in Table 2. Two sets of results are reported in the table: the models with and without portfolio effects, both using the 2SRI method. For each model, the first row exhibits the estimates of the mean parameters for our key variables while the second and the third columns present their interaction effects with transit availability and household size. These interactions allow us to account for cross-region as well as within-region heterogeneity in demand for car ownership. The estimated model also includes make dummies (Toyota, Honda), a used-car dummy, fuel-type dummies (hybrid, diesel), vehicle-type dummies (keicar, minivan), a garage certificate requirement dummy as well as their interactions with metropolitan dummies.

Virtually all parameters are statistically highly significant, and their signs are consistent with economic theory as well as previous studies that estimated similar models.[14] First, the parameter on the logged net income is significantly positive, which implies that consumers with higher incomes are more likely to own cars and that consumers prefer cheaper cars, holding all else constant. Second, the mean parameter on the fuel cost per kilometer (Japanese yen per km, YPK) is significantly negative, which implies that consumers on average value fuel economy. However, its interaction terms suggest that consumers with access to transit density or with large family tend to care less about fuel economy (even after controlling for vehicle size and vehicle types). Third, consumers on average prefer high acceleration. Interestingly, consumers with large family size tend to value acceleration much less. Lastly, though not reported, the keicar dummy is significantly positive, whereas diesel and hybrid car dummies are significantly negative, confirming the Japanese consumers' general preferences for keicars over regular gasoline cars and for gasoline cars over diesel or hybrid cars.

Table 2 also shows the importance of accounting for portfolio considerations — some of the mean and interaction parameters of the portfolio terms are statistically significant. For example, the mean parameter on keicar-keicar combination is significantly negative while that on keicar-regular combination is positive. This suggests that consumers, on average, value the keicar-keicar combination less and the keicar-regular

[14] There is one anomaly that may seem at odds with previous studies in the U.S. — the mean parameter on car size is significantly negative, implying that in Japan, consumers on average value smaller cars. Note, however, that we obtain these estimates after controlling for the vehicle types (i.e., keicars, minivans, etc.) and portfolio effects, which also vary by household size. Hence, the negative sign on car size should be capturing the preferences for the compactness of vehicles within, but not across, vehicle class. Our interpretation therefore is that because the roads and parking spaces are narrow virtually everywhere in Japan (even in rural areas compared to roads in U.S.), consumers on average prefer smaller cars, given their preferred vehicle class. This is consistent with the findings in Konishi and Zhao (2017).

combination more than the regular-regular combination, which we take as the base combination. Their interaction terms with the household size are significantly negative, implying that larger households tend to undervalue these combinations. It is not surprising to see that some portfolio terms are insignificant, for these terms are meant to capture a combination-specific utility that arises only when two vehicles are owned in combination in addition to the value of each individual vehicle.

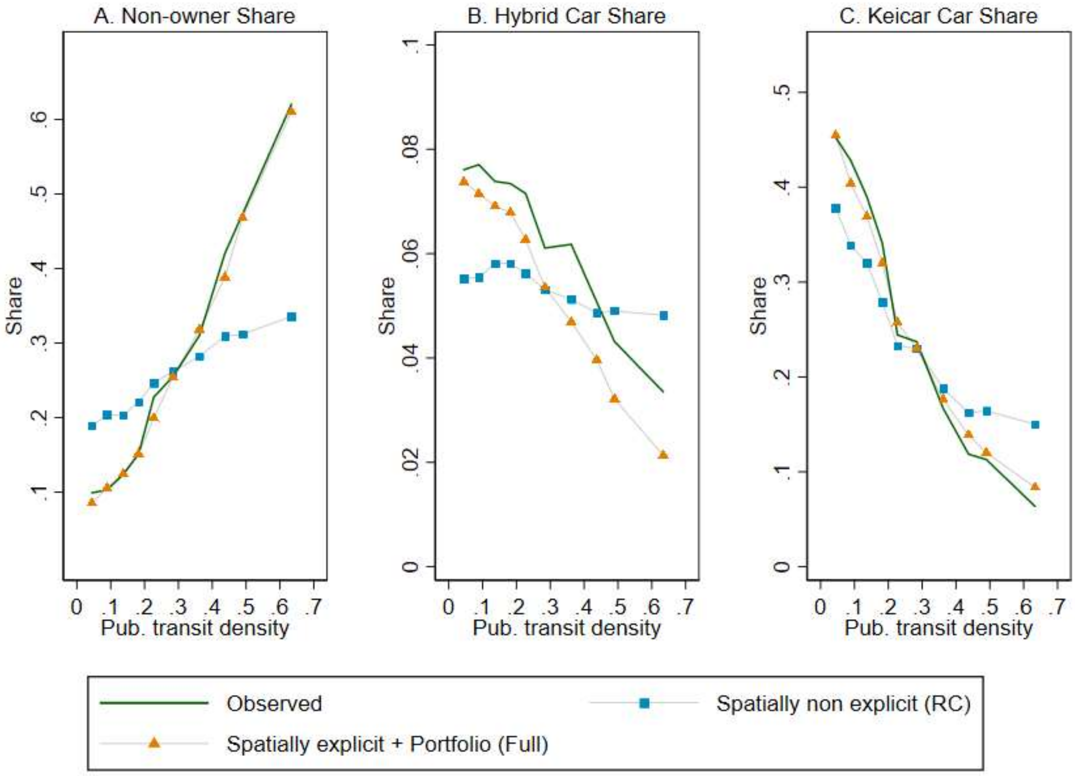
Table 2. Estimation Results on Vehicle Ownership

	No Portfolio Effects			Portfolio Effects		
	Mean Parameter	Interaction Terms		Mean Parameter	Interaction Terms	
		Transit Density	Household Size		Transit Density	Household Size
ln(y-r)	2.377 ***			2.498 ***		
	(0.139)			(0.140)		
YPK	-47.630 ***	6.6806 **	9.462 ***	-45.323 ***	9.222 **	8.342 ***
	(1.441)	(2.983)	(0.400)	(1.503)	(3.045)	(0.412)
HP/W	16.085 ***	24.883 ***	-6.545 ***	16.689 ***	25.720 ***	-6.671 ***
	(1.151)	(1.990)	(0.232)	(1.212)	(2.093)	(0.265)
Size	-0.390 ***	-0.868 ***	0.098 ***	-0.415 ***	-0.888 ***	0.110 ***
	(0.011)	(0.019)	(0.002)	(0.013)	(0.021)	(0.003)
Portfolio Effects						
Kei-Kei				-0.356 ***	-0.230	-0.120 ***
				(0.096)	(0.256)	(0.020)
Kei-Regular				0.213 ***	-0.427 ***	-0.187 ***
				(0.066)	(0.166)	(0.016)
Kei-Minivan				-0.043	0.145	-0.049 ***
				(0.073)	(0.173)	(0.016)
Regular-Regular				0.473 ***	-0.360 *	-0.127 ***
				(0.092)	(0.218)	(0.024)
Regular-Minivan				0.2137 **	-0.601 **	-0.032
				(0.100)	(0.245)	(0.023)
Minivan-Minivan				-0.5837	-0.838	0.121 *
				(0.379)	(0.981)	(0.072)
Obs. (Household x Choice)	13,890,396			13,890,396		
Households	82,730			82,730		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To gauge the importance of accounting for preference heterogeneity over geographic space, we also compare the predicted shares from alternative empirical models against the observed shares by transit density. The first is our full model (the model with spatial interactions and portfolio effects) and the second is the conventional random-coefficient (RC) logit (the model that does not account for spatial heterogeneity or portfolio effects).[15] Figure 2 reports the results of this exercise for three types of ownership: Ownership of any car (panel A), hybrids (panel B), and keicars (panel C). Hence, the figure evaluates the predictive performance on two economic margins: whether or not to own a car and which type of car to own. Note that in these figures, we report on the *unconditional* ownership shares—i.e., not *conditioned* on having a car.

Figure 2. Prediction Performance:
Full Model versus Naïve Random Coefficient (RC) Logit



Note: Predicted shares in this figure are calculated as *unconditional* shares: i.e., not conditional on car holding.

As shown in the figure, the naive RC logit fails to predict all ownership shares by a large margin. We also see a large swing in the prediction errors—i.e., it tends to understate all types of ownership shares in low-density areas whereas overstating them in high-density areas. In contrast, our full model predicts the car ownership share quite precisely for all transit density levels. Importantly, the panel B and C demonstrate that our model does a far better job of predicting the ownership shares of hybrids and keicars, allowing us to explain the empirical patterns discussed in Section II. The accuracy of prediction on these two margins is quite important in simulating the counterfactuals policies in Section VII.

Next, we turn to the vehicle utilization regression. Our focus is on demand elasticities with respect to

[15] To ensure that the differences between our full model and the RC model are only due to spatial interactions and portfolio effects, we incorporate random coefficient terms into our full model.

(net) income and operating cost, and on the influence of public transit density on these elasticities. Table 3 reports the results with income and operating cost (in log) interacted with public transit density and congestion variables. We estimate these regressions with varying levels of controls: metropolitan dummies and selection correction terms. Though the estimates are not reported, all regressions control for other vehicle characteristics (fuel type and car type dummies), demographic characteristics (age, household size, marital status, number of cars owned, work status, distance to work, years of education) and urban structures (district-level population density, access to hospital, and access to public parks). As discussed in Section V, we only report the results with the second-degree polynomials of the highest, the second highest, and the lowest estimated choice probabilities for selectivity correction.

Table 3. Estimation Results on Vehicle Utilization

	(1)	(2)	(3)	(4)
ln(y - r)	0.075 **	0.077 **	0.078 **	0.088 **
	(0.035)	(0.039)	(0.036)	(0.040)
× Transit Density	-0.082 *	-0.096 **	-0.089 **	-0.096 **
	(0.046)	(0.047)	(0.044)	(0.048)
× Congestion	-0.082 *	-0.073	-0.079	-0.088 *
	(0.049)	(0.050)	(0.050)	(0.051)
ln(YPK)	-0.391 ***	-0.433 ***	-0.390 ***	-0.428 ***
	(0.123)	(0.119)	(0.122)	(0.126)
× Transit Density	0.224	0.269 *	0.222	0.278 *
	(0.152)	(0.146)	(0.144)	(0.156)
× Congestion	0.092	0.133	0.088	0.120
	(0.158)	(0.160)	(0.160)	(0.162)
HP/W	0.558	0.493	0.553	0.470
	(1.339)	(1.281)	(1.358)	(1.326)
Size	0.272 ***	0.277 ***	0.273 ***	0.278 ***
	(0.044)	(0.045)	(0.044)	(0.044)
Second Car	-0.210 ***	-0.210 ***	-0.211 ***	-0.210 ***
	(0.032)	(0.033)	(0.032)	(0.032)
Demographic controls	✓	✓	✓	✓
Urban structure controls	✓	✓	✓	✓
Metropolitan dummies			✓	✓
Selection controls		✓		✓
χ^2-stat. on selection terms	-	51.35 ***	-	40.38 ***
Obs.	21,456	21,456	21,456	21,456
R^2	0.076	0.078	0.077	0.079

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The estimate of the mean income elasticity is always positive and statistically significant.[16] Furthermore, the income elasticity is smaller for consumers living in high density areas. This makes sense since recreational value of driving would be larger for consumers who have limited access to in high public transit. Note that we can focus on leisure-related arguments as we already control for distance to work. As we discuss in more depth below, the gradient of this income elasticity has an important implication for design of carbon revenue rebates.

The estimate of the mean price elasticity is negative and statistically significant across all specifications. This is not only consistent with economy theory, but suggests the success of our control strategy—in studies that use cross-sectional household-level data, this elasticity is often estimated with bias toward zero or even positive [e.g., Goldberg (1998)]. The interaction with public transit density is positive and marginally significant. This suggests that the demand for driving is less price-elastic in high density areas. This may seem somewhat counter-intuitive at first. When the price of gasoline increases, for example, consumers who have access to public transit can use public transit instead of driving, and therefore, we would expect the demand for driving to be more price elastic in areas with high public transit density. This logic ignores the income effect. Consumers with access to public transit use cars primarily for a recreational purpose, and the fuel cost accounts for a relatively small portion of the recreational expenditures. On the other hand, consumers with limited access to public transit use cars for daily use, and the fuel cost accounts for a larger share of consumer expenditures. Hence, this makes the demand for driving more price-elastic for consumers in areas with low public transit density.

With all specifications, the selectivity correction terms are jointly highly significant. This is despite the fact that we already control for a number of observables. Moreover, inclusion of these correction terms generally improves the statistical significance of our key parameters. This implies that there is selection on unobservables, and thus, omitting selection correction terms is likely to bias our estimates. When translating these parameter estimates into elasticity estimates by public transit quintile, this gain in consistency does seem to matter. Hence, we are in general in favor of models with selection correction.

Lastly, we also note that our empirical model explains not only the spatial distribution but also the temporal variation of automobile demand quite well. In our companion paper (Konishi and Kuroda, 2023), we use the estimated model to "predict" the past distribution of car ownership and utilization at the *district level for each year from 1990 to 2015 using the district-level demographic data.* The prediction from the model, despite being quite disaggregate, can explain the aggregate time path of car-related CO_2 emissions for the 25-year period surprisingly well. Such a high explanatory power of our model for both the spatial and the temporal variation of the Japanese automobile demand gives us confidence for its use in the counterfactual policy simulation.

[16] The estimate becomes insignificant when we exclude the congestion interaction term. This makes intuitive sense. When a household's income increases, the household would increase her time to allocate for leisure, but how much she would increase time to spend on driving depends on how congested roads are. She would drive more if roads are less congested.

VI-2. Elasticity Estimates

Table 4 reports the estimated elasticities of vehicle CO_2 emissions with respect to *price* (per-unit driving cost) and *income* by income and public transit quintiles. These elasticities are reported in Panels C and D while panels A and B report the price and income elasticities of vehicle ownership for reference. The expected CO_2 emissions are calculated as follows:

$$E_i = \sum_{j \in J} \varphi_j \hat{m}_{ij} \hat{P}_{ij}$$

where φ_j is the engineering estimate of CO_2 emissions per unit of driving distance, $\hat{m}_{ij}$ is the predicted annual driving distance, and $\hat{P}_{ij}$ is the predicted ownership share of model j by household i. We then apply the standard elasticity formula for vehicle ownership $\hat{P}_{ij}$ and utilization $\hat{m}_{ij}$, using the estimates from Table 2 and 3 and averaging over households in each subsample. Note that by definition, this CO_2 elasticity combines two elasticities, ownership and utilization, on which household incomes and public transit availability may have quite different impacts.

Table 4 indicates several important results that become crucial for our subsequent simulation work. First, the estimated income elasticities of ownership range from 0.02 to 0.33, and are higher for low-income consumers, holding public transit density. This is consistent with both economic theory and graphical evidence presented in Figure 1. Combined with driving distance elasticities, these elasticities translate into the income elasticities of CO_2 emissions. The estimated income elasticities of CO_2 emissions are positive,[17] but are economically small, suggesting that the perverse effect of carbon revenue rebates is likely small.

Second, holding income, the income elasticities of car ownership are generally higher for areas with higher public transit density, yet the same is not true about the CO_2 emissions elasticities. This is because the income elasticities of driving distance tend to decline with public transit density, particularly for higher-income households. This makes intuitive sense: When additional income is given to a household, the household is less likely to spend it to increase driving in high-transit-density areas than in low-transit-density areas, and much less likely so if the household is wealthier. This signifies the difficulty (and importance) of designing the place-based rebate scheme, for it suggests that the perverse effect of rebates is generally not a monotonic function of public transit density (even after holding income).

Third, the elasticities of car ownership with respect to driving cost are higher for lower-income households (holding public transit density) and lower for households in lower-transit-density areas (holding income). This is also consistent with both economic theory and graphical evidence presented in Figure 1. The estimated elasticities are in the economically reasonable range and quite similar to those of the previous

[17] An exception is in the fifth public transit quintile, which occurs due to the negative, but statistically insignificant estimate of driving distance elasticity.

Table 4. Ownership and CO_2 Elasticity Estimates by Income and Public Transit

Public Tansit Density (Quintiles)	Income (Quintiles)					All
	1st (Lowest)	2nd	3rd	4th	5th (Highest)	
Panel A. Elasticity of Ownership w.r.t. income						
1st (Lowest)	0.168	0.065	0.042	0.028	0.017	0.066
2nd	0.187	0.074	0.048	0.032	0.020	0.071
3rd	0.227	0.090	0.058	0.038	0.023	0.082
4th	0.277	0.115	0.075	0.049	0.030	0.095
5th (Highest)	0.327	0.147	0.098	0.066	0.039	0.122
All	0.233	0.096	0.063	0.043	0.027	0.087
Panel B. Elasticity of Ownership w.r.t. price (per unit driving cost)						
1st (Lowest)	-0.374	-0.160	-0.107	-0.073	-0.046	-0.156
2nd	-0.423	-0.178	-0.119	-0.080	-0.050	-0.168
3rd	-0.508	-0.214	-0.140	-0.094	-0.058	-0.189
4th	-0.611	-0.273	-0.179	-0.120	-0.072	-0.220
5th (Highest)	-0.698	-0.337	-0.227	-0.156	-0.093	-0.272
All	-0.514	-0.227	-0.152	-0.104	-0.067	-0.202
Panel C. Elasticity of Carbon Emissions w.r.t. income						
1st (Lowest)	0.183	0.087	0.065	0.051	0.039	0.087
2nd	0.191	0.081	0.056	0.040	0.027	0.078
3rd	0.218	0.082	0.050	0.030	0.014	0.073
4th	0.252	0.092	0.051	0.025	0.004	0.071
5th (Highest)	0.284	0.104	0.054	0.021	-0.008	0.077
All	0.223	0.089	0.055	0.033	0.012	0.077
Panel D. Elasticity of Carbon Emissions w.r.t. price (per unit driving cost)						
1st (Lowest)	-0.777	-0.525	-0.460	-0.418	-0.382	-0.518
2nd	-0.805	-0.517	-0.442	-0.393	-0.353	-0.499
3rd	-0.864	-0.523	-0.432	-0.373	-0.327	-0.487
4th	-0.932	-0.546	-0.433	-0.361	-0.299	-0.477
5th (Highest)	-0.971	-0.562	-0.433	-0.347	-0.268	-0.480
All	-0.864	-0.533	-0.441	-0.378	-0.319	-0.492

Note: Panel A and B report the elasticity of car ownership (the number of cars owned) with respect to income and driving cost while Panel C and D report the elasticity of CO_2 emissions.

studies. As with income elasticities, however, these elasticities do not directly translate into the CO_2 emissions elasticities. Driving distance elasticities (see Table 3) are much larger than ownership elasticities, and as a result, the CO_2 elasticities are generally larger than ownership elasticities (in the range of 0.30-0.97). Furthermore, the CO_2 elasticities with respect to driving cost decrease monotonically with income, but not with public transit density. This is somewhat unexpected and has an important implication for both the incidence (welfare cost) of carbon tax and the design of rebate schemes. In the lowest income quintile, the estimated CO_2 elasticities are smaller for lower-transit-density areas, implying that the welfare cost of carbon tax is higher for these areas. The opposite is true in the highest income quintile while the elasticities are similar across areas in the middle-income quintiles. Averaging across all income groups, higher-transit-density quintiles have *smaller* CO_2 elasticities than the lowest-transit-density quintile. From the equity perspective, giving more rebates to those with less elastic demand is welfare-improving *ceteris paribus*, yet the same amount of rebate is more valuable to those with lower incomes. Hence, it is empirically quite ambiguous whether giving more rebates to households in higher-density areas or lower-density areas is more welfare-improving. This is the question we turn to in the next section.

VII. Income-based versus Place-based Rebates

VII-1. Counterfactual Scenarios

We now use the estimated model to simulate the distributional impacts of counterfactual carbon tax-and-rebate policies over geographic space. There is already a large literature that empirically investigates the distributional consequences of automobile-related economic policies [e.g., West (2004), Bento *et al.* (2009)]. Their focus is, however, on the variation of policy impacts by income. In contrast, what we wish to demonstrate here is that public transit availability and innate preferences for vehicle portfolios may interact with income distribution over geographic space in such a way that generates important implications for efficiency and equity of alternative carbon revenue recycling schemes. To that end, we consider the carbon tax of \$50 per ton of CO_2 with alternative rebate schemes: (a) a flat allocation, (b) an income-based allocation, and (c) place-based allocation based on the transit density.

We assume that a tax is implemented on top of the existing tax on gasoline, and that all tax revenues are fully rebated to households, as in other studies [see, for example, Andersson (2019) for the case of Sweden and Bento *et al.* (2009), for the case of the U.S.]. We use \$50 per ton of CO_2 as a benchmark estimate of social cost of carbon emissions (SCC) per Revesz *et al.* (2017). Online Appendix D provides the results with the carbon tax of \$200, a SCC value more consistent with the recent SCC literature [Rennert *et al.*, 2022; EPA, 2023]. In theory, the SCC-based carbon tax on gasoline can fully restore economic efficiency by correcting for the negative externality associated with carbon emissions from vehicle transportation. Note that to maintain economic efficiency, the transfer *should be made in a lump-sum manner: it should not* be based on car ownership or VKT.

Regarding the income-based scheme (b), there is a question as to whether the rebates should be an increasing or decreasing function of income. Bento *et al.* (2009) considers the income-based revenue recycling where rebates are an *increasing* function of income because households with higher incomes tend to have inelastic automobile demand. Our elasticity estimates in Section VI also confirm that both price and income elasticities of car ownership as well as CO_2 emissions decrease with income, holding public transit density. Hence, following Bento *et al.* (2009), larger rebates are given to higher-income households in the income-based allocation scenario. See Online Appendix D for how we calculate the rebates.

Turning to the place-based scheme (c), we have seen in Section VI that these elasticities also depend crucially on the public transit density of the areas where households live. For the lower-income households (the 1st and 2nd quintiles), both the *income* and the *price* elasticity of CO_2 emissions tends to increase with public transit density. This suggest that for the lower-income households, giving more rebates to lower-transit-density areas is likely to minimize not only the perverse demand-inducing effect of rebates but also the adverse welfare effect of carbon tax. Furthermore, because these lower-income households also spend a larger share of income on car ownership and utilization than the higher-income households, the same amount of rebates would be more valuable to those households. Given these, the place-based scheme is designed to allocate more rebates to lower-density households. Our Online Appendix D explains the details of the rebate scheme as well as the results of alternative place-based rebate schemes.

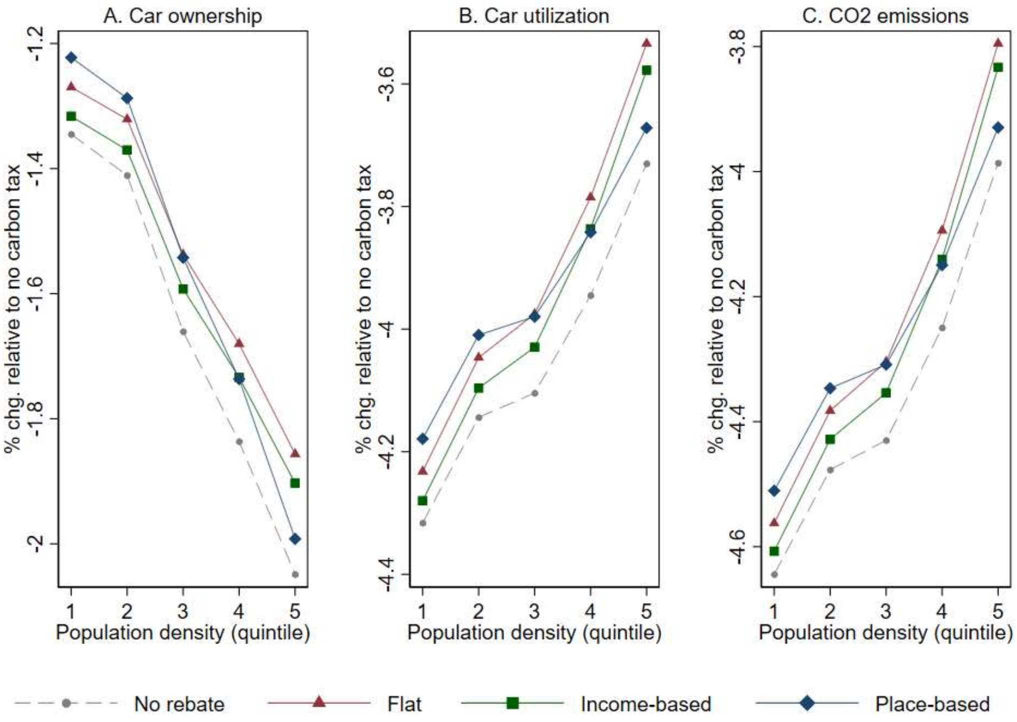
Our outcome variables of interest are vehicle ownership (number and types of cars owned), vehicle utilization (annual vehicle kilometers traveled), carbon emissions (annual CO_2 emissions from vehicle utilization), and consumer welfare (to be defined below). Note that our ability to simulate economic outcomes is limited to those that make use of demand-side parameters only. We have neither data nor policy relevant variations to estimate the supply-side parameters with respect to the public transit. Therefore, in the analysis below, we assume perfectly inelastic supply-side responses, and treat car prices, gasoline prices, and any other economic outcomes that would require supply-side parameters as 'fixed', as in other studies [e.g., West (2004); Ferriere *et al.* (2023)]. Consequently, our simulated outcomes should not be taken as realistic equilibrium responses to the counterfactual policies. Our goal here, instead, is to signify the importance of accounting for spatial distribution of automobile demand for designing efficient and equitable climate mitigation policies.

VII-2. Results of Counterfactual Simulations

We start by presenting the impacts of the carbon tax-and-rebate policies on three outcomes in Figure 3: (A) car ownership, (B) car utilization, and (C) vehicle CO_2 emissions. For each outcome, we display percentage changes under four counterfactual policy scenarios relative to the no-policy benchmark. In the figure, the means are reported against population density deciles. We do this because our interest lies in understanding how incomes, public transit, and portfolio preferences interact to generate intricate spatial heterogeneity over geographic space, a simple measure of which we use is population density.

The figure signifies two primary findings. First, as expected, the carbon tax is more effective in reducing CO_2 emissions in non-urban areas than in urban areas. This occurs due to the intricate interaction between income, public transit, and portfolio preferences. On one hand, residents in non-urban areas have inelastic

Figure 3. Heterogeneous Impacts of Counterfactual Policies over Geographic Space



Note: The vertical axis is the percentage change under each counterfactual relative to the no-policy benchmark. We use the SCC value of \$50/ton-CO_2. There are four scenarios for revenue recycling: no rebate, flat rebate, and rebate based on income or public transit density.

demand for car ownership, and therefore, the carbon tax is not as effective in reducing car ownership in such areas. On the other hand, conditional on car ownership, car utilization is more elastic in non-urban areas, and hence, the carbon tax is more effective in reducing car utilization in such areas. These results make intuitive sense. Residents of non-urban areas cannot stop owning cars due to limited public transit availability, and hence, respond to the car tax by reducing car utilization instead of reducing car ownership. The opposite occurs in urban areas.

Second, revenue recycling generally increases car ownership and utilization (due to the income effect), inducing higher CO_2 emissions than no recycling. The effects differ substantially across different rebate schemes, however. Relative to the flat rebate, the income-based recycling (with rebates increasing in income) tend to decrease both car ownership and utilization, thereby inducing more CO_2 emissions, in *all* areas. This occurs because the income elasticity of demand is estimated to be lower for high-income households than for low-income households so giving more rebates to higher-income households decreases CO_2 emissions. In contrast, the place-based recycling (with rebates decreasing in public transit density) tends to increase both car ownership and utilization in *non-urban* areas but decrease them in urban areas, relative to the flat scheme. As a result, the overall CO_2 emissions are slightly higher under the place-based rebates than the flat or income-based rebates. This occurs precisely because the income elasticity of demand is generally higher in non-urban areas than in urban areas so giving more rebates to non-urban areas results in higher CO_2 emissions. However, the perverse demand-inducing effect of rebates is quite small overall under all schemes because our estimated income elasticities are small.

Let us turn to consumer welfare. Economic theory predicts that consumers with inelastic demand would have higher tax incidence, and thus, lose more from a given tax level. While the carbon dividend mitigates these welfare losses, the extent to which it offsets them depends on the elasticities implied by the estimated demand model. Consequently, consumers' welfare losses vary by income level and region of residence. The key question here is how welfare losses vary by income level and region, and how rebates under various scenarios compensate these welfare losses. Since our demand model is based on a random utility model, we can calculate the consumer's compensating variation using the formula a la Small and Rosen (1981). A challenge, however, is that our specification involves a non-linear income term, and thus, we do not have a closed-form analytical expression for the compensating variation. We thus follow Herriges and Kling (1999) and solve for it numerically.

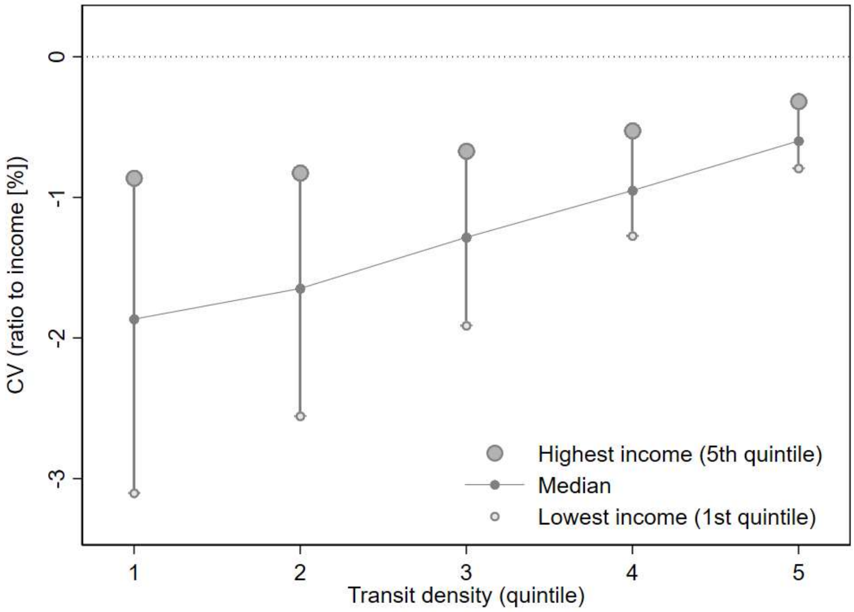
Panel A of Figure 4 illustrates how a policy without rebates affects consumer welfare by income and public transit density. In this figure, we quantify the compensating variation as a percentage of household income and plot the estimates for the lowest income quintile, the median, and the highest income quintile within each public transit density quintile. As expected, the figure reveals substantial heterogeneity in welfare losses by income level and region. Tax incidence is higher in non-urban areas and is more pronounced in low-income households. Notably, the difference in welfare loss between the lowest and highest income quintiles is 3.5 times larger for the lowest-transit-density areas than for the highest-transit-density areas.

Panel B compare the welfare gains from different rebate schemes relative to the no-rebate scenario. As expected, the flat rebates improve consumer welfare for all areas and all income groups relative to no such rebate. Compared to the flat scheme, the welfare-improving effects of the income-based allocation are much smaller for all areas. This occurs because the income-based scheme allocates more rebates to high-income households and the welfare gain is quite small for these households when expressed as a percentage of their income. In contrast, the place-based allocation substantially improves welfare for all income groups in the low-transit-density areas. The welfare-improving effect of the place-based scheme is quite small for the high-transit-density areas, but the welfare losses from the carbon tax for these areas are also quite small as shown in Panel A. Therefore, the place-based rebate scheme generates the greater overall welfare gain than the flat or the income-based scheme.

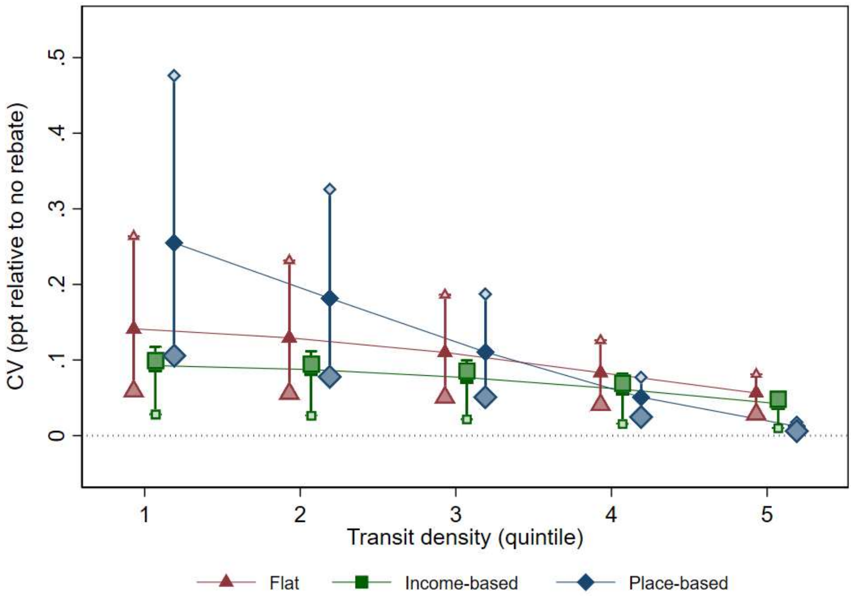
Table 5 reports the impacts of the alternative revenue recycling schemes on aggregate social welfare. All values in this table, except for vehicle CO_2 emissions, are reported in Japanese yen (JPY) on a per household basis in relative terms to the no-rebate scenario. As discussed in Section II, there is an inherent

Figure 4. Impacts of Counterfactual Policies on Consumer Welfare over Geographic Space

Panel A. The Welfare Effect of Carbon Tax without Rebate Relative to No Tax (Status Quo)



Panel B. The Welfare Gains from Alternative Rebate Schemes Relative to No Rebate



Note: Panel A shows the compensating variation (CV) as a percentage of household income for a carbon tax policy without rebates relative to no carbon tax scenario. Panel B shows the percentage point change in consumer welfare (CV as a percentage of income) with a rebate scheme relative to no rebate. The whiskers represent the range of values calculated for different income levels. The large markers (△ etc.) represent the average value for households in the highest income quintile while the small markers (▵ etc.) represent the average value for households in the lowest income quintile.

Table 5. The Overall Average Impacts of Counterfactual Policies

Counterfactual Policy	CO_2 Emissions (ton-CO_2/yr)	Chg. in Consumer Welfare (JPY) (a)	Chg. in CO_2 Damages (JPY) (b)	Chg. in Social Welfare (JPY) (a) + (b)	Rebate Amount (JPY)
Carbon Tax with No Rebate	1.357	--	--	--	--
Carbon Tax with Rebates					
Flat-Rebate	1.359	+4,615	-12.1	+4,603	6,733
Income-Based Rebate	1.358	+4,885	-7.2	+4,878	6,733
Place-Based Rebate	1.359	+5,280	-12.7	+5,268	6,733

Note: All values are annual averages per household. Columns (a) and (b) correspond to $\tau\omega\Delta y$ and $u_c\Delta y$ discussed in Section II.

trade-off in designing the rebate scheme: We wish to give more rebates to consumers with the greatest welfare loss from the carbon tax, but doing so might have a perverse effect of inducing demand for vehicle CO_2 emissions. We have seen from Figure 3 that the place-based scheme tends to increase vehicle CO_2 emissions in low-density areas more than the flat or the income-based schemes. We have also seen from Figure 4 that the gain in consumer welfare from the place-based scheme in low-density areas (relative to other rebate schemes) tends to outweigh the loss in high-density areas. The key question then is whether the place-based allocation remains the better policy option even after accounting for the negative externality cost of increasing the vehicle CO_2 emissions. Table 5 confirms that it is indeed the case, along with other important take-aways.

First, the carbon revenue rebates increase consumer welfare, but the effect is not necessarily large. The magnitudes of the welfare impact range from 4,615 yen to 5,280 yen, capturing roughly 70-80% of the average rebate. Second, the perverse (demand-inducing) effect of rebates is negligibly small at least on a per capita basis. The increase in CO_2 emissions damages due to the rebates range from 7.2 yen to 12.7 yen. This does not mean, however, that the effect is small to everyone. There are a large number of households without cars whose vehicle CO_2 emissions don't change in response to rebates. Hence, averaging over households results in a small increase per capita. Third, the place-based allocation outperforms both the flat and the income-based rebates (and no-rebate) in terms of aggregate social welfare because the welfare increasing effect of the rebates dominates the perverse CO_2-increasing effect. Lastly, though not reported in the table, the estimated welfare loss from the carbon tax without the rebates is roughly 60,000 yen (approximately 400 USD) per household.[18] This welfare loss is much larger than the average tax payments

[18] We also compare our simulation results with those of Bento *et al.* (2009), who studied the distributional effects of a gasoline tax in the United States. Comparing theirs with ours using the same tax rates, their estimated welfare losses *without* the rebate are higher than ours whereas the welfare losses *with* the rebates are lower than ours. This difference essentially comes from the differences in the estimates of price and income elasticity. We refrain from making any judgement on the

or the welfare gain from the rebates. This implies that even if “average” consumers receive more rebates than their tax payments, their utility loss is greater than the net rebates so they still lose from the carbon tax. These findings not only echo our theoretical discussions in Section II, but may also explain why the social acceptance of carbon tax policies is very low in Japan.

VIII. Conclusion

Economists are increasingly confronted with the fundamental difficulties associated with the design of climate mitigation policies. We would like the policies to be sufficiently effective, and ideally, economically efficient. Yet, effective and efficient policies are not necessarily the ones that receive wide support from politicians and citizens in real-world settings. The Yellow Vest Movement in France exemplifies such difficulties economists and policy practitioners face today. Japan has also been increasingly recognized as the country that shows low support for strong climate policies (UNDP, 2024). How best to design climate mitigation policies given the important trade-off between efficiency and equity is, thus, a highly policy-relevant question, both worldwide and in Japan.

With this broader question in mind, we empirically investigate the carbon tax-and-rebate policy for automobiles in Japan. We estimate a model of vehicle ownership and utilization, explicitly accounting for the role of incomes, public transit networks, and portfolio considerations, using a large cross-section sample of households in Japan. The model allows us to characterize how the automobile demand varies over geographic space as well as how the economic impacts of tax-and-rebate policy depend on such spatial demand heterogeneity. We then use the estimated model to simulate the distributional impacts of alternative rebate schemes (flat, income-based, and place-based revenue recycling) on carbon emissions and consumer welfare.

The estimation of the model reveals several important results that are critical for our simulation work. The estimated price and income elasticities of car ownership decrease with household income levels (holding public transit density) and increase with public transit density (holding household incomes). The elasticities of CO_2 emissions (incorporating car utilization), however, do not monotonically increase or decrease with public transit density (holding household incomes). This makes it empirically quite ambiguous how the place-based rebate scheme performs relative to other rebate schemes. Our results also indicate that the demand for vehicle CO_2 emissions is relatively inelastic. This suggests both the potentially high incidence (welfare loss) of carbon tax and the potentially small welfare-increasing effect of revenue rebates. Our results also indicate that consumers in low-density areas inelastically demand *keicars* (i.e., extremely small vehicles) for its cost-effectiveness and that all three factors—incomes, public transit, and portfolio considerations—are important in generating this inelastic demand.

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difference because our study context is quite different from theirs.

Our simulation also reveals several important findings. First, the rebates tend to increase CO_2 emissions by inducing vehicle transport demand, but the perverse effect is quite small. Hence, our result supports the general view that the demand-inducing effect of rebates is not a major threat to the design of rebate schemes. Second, the rebates do increase consumer welfare, but the welfare-enhancing effect of rebates are not large enough to offset the welfare loss from the carbon tax. This result is driven by the inelastic automobile demand particularly in non-urban areas—the low price elasticity drives the large welfare loss from the carbon tax while the low income elasticity drives the small welfare gain from the rebates. Third, the place-based rebate scheme outperforms all other schemes (no rebate, the flat rebate, and the income-based rebate schemes). The place-based scheme allocates more rebates to consumers in lower transit density areas subject to the government revenue neutrality constraint. This tends to induce larger CO_2 emissions from low-density areas than other schemes, yet the effect is negligibly small because of the relatively small income elasticity estimates. In the meantime, the place-based rebates improve the consumer welfare of the most severely affected households, i.e., those in non-urban areas who lack access to public transportation services, and do so more than in other schemes. As a result, the overall social welfare is higher under the place-based scheme than any other schemes. We believe that these results provide important insights for economists and policy practitioners whose interest lie in better social acceptance of carbon pricing and climate justice.

Lastly, there are several important limitations to our study. First, our analysis is limited to the demand side only. Neither supply-side responses (e.g., price/quality changes) nor producers' surplus is accounted for in our simulation. This can be addressed only with availability of suitable data, and thus, is left for future research. Second, we only consider a limited set of revenue recycling methods, focusing on income and public transit density as primary attributes. We deliberately made this choice partly due to the limitation of our data and empirical model and partly because this focus provides better realistic contexts for broader audience. Ideally, we would set up the regulator's optimization problem, choosing from a full set of schemes, which potentially combine multiple dimensions other than income and public transit, in order to maximize social welfare subject to the revenue neutrality constraint. This is an important direction of research left for future research.

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Online Appendix for

Income-based or Place-based?

Carbon Dividends under Spatial Distribution of Automobile Demand

by Yoshifumi Konishi, Sho Kuroda, and Shunsuke Managi

Appendix A. Details for Model

This appendix complements Section III.

A1. Correction of Selection Bias in Vehicle Mileage (VKT) Equation

It is known that OLS regression of eq. (3) would generally give us biased estimates of parameters due to sample selection. To see this in our empirical setup, note that we can write $v_{ijs} = E[v(m_{ijs})|X_i, Z_j, S_{is}] + e_{ijs}$, and hence, the error term ϵ_{ijs} in eq. (1) is confounded with another error term e_{ijs}, forming the joint error term $\mu_{ijs} \equiv e_{ijs} + \epsilon_{ijs}$. Consequently,

$$E[\eta_{ijs}|X_i, Z_j, S_{is}, j \text{ is chosen}] = E[\eta_{ijs}|V_{ijs} + \mu_{ijs} \geq V_{iks} + \mu_{iks} \text{ for all } k] \neq 0$$

where V_{ijs} is the observable part of the indirect utility, and the last inequality follows because η_{ijs} contains some of the information in e_{ijs}, the unobserved part of utility from driving car model j. Simply put, consumers would enjoy driving cars of their favorites and not so much for others. To address the selection problem, we use Dahl's (2002) control function approach. Refer to the main text for more details.

We can incorporate the portfolio effect into the sample correction terms in the vehicle mileage eq. (4) by slightly modifying our notation. Let J_1 and J_2 be the sets of products for her first and second cars, respectively. Let us augment J_2 by including 'zero', an option to own no second car. Adjoining these two sets and an outside option to own no car, we create the joint choice set J, which contains $1 + \#J_1 \times \#J_2$ alternatives. The consumer chooses an alternative j from this adjoined set. That is, one may choose to own no car $(0,0)$, choose to own one car $(j_1, 0)$, or choose to own two cars (j_1, j_2). With a slight abuse of the notation, (j, k) in place of j, the model described by eq. (1) and (4) is essentially intact.

Appendix B. Choice Set and Key Variables

This appendix explains how we define the choice set for the vehicle ownership estimation and key variables used in estimation. We classify each respondent's observed vehicle choice according to its curb weight, car type, fuel type, sales type, and make as in Table B.1. We do essentially the same for the first and the second most frequently used cars. We exclude from the choice set alternatives that are only chosen by less than 60 households; we further confirm that this setting is robust to our estimations. This yields a choice set of 168 alternatives (incl. the option of holding no car). Vehicle attributes such as displacement, horsepower, size, and weight are averaged over observations for each choice alternative. Price variables (i.e., rental price and YPK) are similarly averaged over observations for each choice alternatives and then adjusted to contemporaneous values using information on purchase year/month (see below). This type of aggregation is common in studies that use household-level data [see, for example, Bento *et al.* (2009)]. Even with this level of aggregation, Stata's maximum likelihood estimation of the conditional logit model takes roughly 1 hour for each run on a modern computer (10 cores/20 threads, Core i9 CPU, 64GB memory), due partly to our large sample size. Intuitively speaking, this aggregation implies that the consumer in the model makes her choice comparing the choice of her own against 'average' economic values of alternatives.

Table B.1. Vehicle Classification

U.S. NHTSA Classification	Car Type	Fuel Type	Sales Type	Make
Mini: Weight ≤ 900 (kg)	Keicar	Diesel	New	Toyota
Light: 900 < Weight ≤ 1,150	Regular	Hybrid	Used	Honda
Compact: 1,150 < Weight ≤ 1,350	Minivan	Gasoline		Other
Medium: 1,350 < Weight ≤ 1,600				
Heavy: Weight > 1,600				

Our key variables used in estimation (both the ownership and the utilization equation):

Household income: Annual before-tax incomes are reported with an interval of 1 million yen from 2 million yen up to 10 million yen, and then 10 to 15 million yen, 15 to 20 million yen, and 20 to 30 million yen. We use the mid-point of income interval as a measure of annual income.

Rental price: The survey records the purchase price of each of the two frequently used cars. We convert the purchase price into a rental price using an annual depreciation rate of 10% and annual interest rates, which is allowed to vary by year/month of purchase. We add annualized automobile taxes and tax incentives to this rental price, which are also allowed to vary by year/month of purchase. The rental price is further adjusted for regional inflation rates.

Household size: We use the raw number of individuals in the household.

Yen per kilometer (YPK): YPK is the gasoline price divided by the catalog-based fuel economy ratings. We use the gasoline price for the year/month of purchase.

Horsepower/weight (HP/W): HP/W is the horsepower divided by curb weight.

Size: Vehicle size measured as the sum of length, height, and width.

Garage certificate dummy: In Japan, basically all vehicles must obtain a garage certificate, but in some areas, only keicar do not require a garage certificate. Since a garage certificate is required to prevent on-street parking, areas where it is not required are generally considered to have sufficient parking space, and such areas may have high demand for vehicles in terms of ownership costs and ease of driving.

Metropolitan dummies: Four dummy variables indicating whether the respondent resides in major metropolitan areas: Kanto, Chukyo, Kinki, or Kitakyushu.

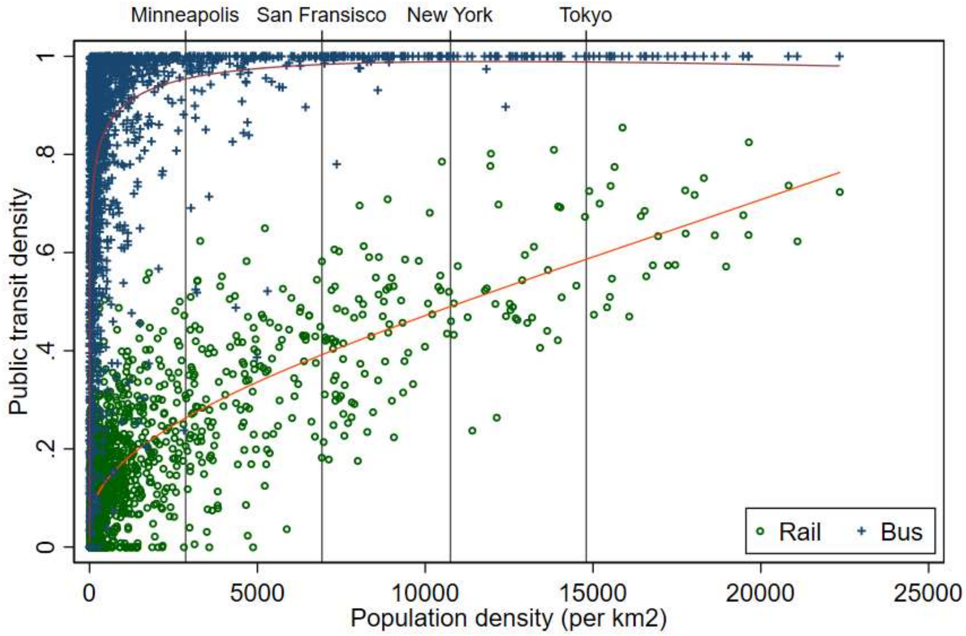
In the vehicle utilization equation, we also use (1) the respondent's age, years of education, work status, marital status as demographic controls and (2) population density and availability of hospitals and public parks at the district level as geographic controls.

Public Transit Density: One of the variables describing geographical heterogeneity is a composite measure of accessibility to public transit. See footnote 2 in the manuscript for the definition of this variable.

We use the public transit variable based on railways in our estimation rather than the variable based on buses. We explain the reasons for this based on Figure B.1. This figure displays two scatter plots: the composite index and a similar index using bus network, both against the population density using district-level observations. The figure demonstrates that the composite index using railways has an increasing, but non-linearly relationship to population density while the index using buses has very little geographic variation and its inclusion would misleadingly overstate public transit accessibility. Hence, we use this index as the measure of public transit density.

Furthermore, we confirm by additional analysis that the extension of the model to include a public transport density variable created based on the bus network does *not* change the estimation results and the primary econometric consequences and its interpretations.

Figure B.1. Public Transit Density vs. Population Density in 2015



Note: All observations are at the municipality level. For reference only, we use county- or city-level population density data for US cities.

Appendix C. Estimation and Identification Issues and Two-stage Residual Inclusion (2SRI) Method

Public transit: In the literature, it is often assumed that public transit is predetermined prior to their car-holding decisions. Indeed, these measures are known to work better than other forms of urban structures (see Bento *et al.*, 2005). However, there is still a concern that households' intrinsic preferences for car holdings may be correlated with measures of public transit—households may make residential choice in conjunction with choice of car holding. To address this concern, we exploit the idea that the public transit network in the past is generally a good instrument (e.g., Duranton and Turner, 2011). There are, however, two limitations with the conventional IV approach in this context. First, the correlation between the public transit measure and the unobservable errors makes *all* of its interaction terms endogenous. Hence, the conventional IV strategy would require a large number of instruments. Second, it is known that a 'plug-in' 2SLS method produce inconsistent estimates in nonlinear models such as this. Terza *et al.* (2008) and Wooldridge (2015) discuss how an alternative two-stage residual inclusion (2SRI) method can overcome these limitations. In our estimation, we further exploit the parsimonity of the 2SRI approach using the 1980 railway networks as instrument to address virtually all endogeneity concerns that arise through consumer's endogenous residential decision.[19]

The full specification of our conditional logit model is given by:

$$u_{i(j,k)s} = \rho \ln\left(y_i - r_{ij} - r_{ik}\right) + \mathbf{Z}_j'(\lambda_0 + x_i\lambda_1 + tr_s\lambda_2) + \mathbf{Z}_k'(\lambda_0 + x_i\lambda_1 + tr_s\lambda_2) \\ + (\kappa_0 + \kappa_1 x_i + \kappa_2 tr_s)I(j,k) + \epsilon_{i(j,k)s}$$

where x_i is the household size and tr_s is the rail transit density. The $I(j,k)$ term is an indicator denoting that the combination of car model j and k is held.

Our concern is the endogeneity of tr_s that arises through consumer's endogenous residential decision. Consumers who reside in low transit areas may have innate preferences for driving; those who reside in high transit areas may have innate distastes for driving. Such innate preferences may correlate with preferences for certain types of cars, and hence, enter the indirect utility as a choice-specific unobserved error $\epsilon_{i(j,k)s}$. The 2SRI method we describe below can parsimoniously address all endogeneity concerns that arise through consumer's endogenous residential decision.

Let $\mathbf{w}$ be a vector of valid instruments for tr_s such that:

---

[19] Needless to say, our model and data do not represent *all* the factors that determine automobile demand, and there are some factors that are not explicitly considered in the model: regional industrial structure, the presence of large shopping malls, one car per person in rural areas (or, in addition, owning a light truck), etc. An important objective of out work it to achieve unbiased estimation of parameters related to the price elasticity and the geographic heterogeneity term (the cross term with public transit density) of the demand system, and the 2SRI is useful to this end.

$$tr_s = g(\mathbf{w}) + \nu_s \quad \text{and} \quad E\left[\epsilon_{i(j,k)s} \middle| \mathbf{w}\right] = 0.$$

Let us further assume that we can write

$$E\left[\epsilon_{i(j,k)s} \middle| \nu_s\right] = \Lambda_{i(j,k)} \nu_s.$$

Note that we are exploiting the fact that the pure source of endogeneity lies at the district level (i.e., innate preferences for choosing district s), yet is correlated with choice-specific unobservables. Wooldridge (2015) shows that in nonlinear models, we can flexibly apply the control function approach and rewrite the indirect utility as:

$$\begin{aligned} u_{i(j,k)s} = \rho \ln\left(y_i - r_{ij} - r_{ik}\right) + \mathbf{Z}_j'(\lambda_0 + x_i\lambda_1 + tr_s\lambda_2) + \mathbf{Z}_k'(\lambda_0 + x_i\lambda_1 + tr_s\lambda_2) \\ + (\kappa_0 + \kappa_1 x_i + \kappa_2 tr_s) I(j,k) + \nu_s + \nu_s^2 + \Lambda_{i(j,k)}\nu_s + \Lambda_{i(j,k)}\nu_s^2. \end{aligned}$$

Given this, we implement this 2SRI method as follows. In the first step, we fit the fractional polynomial regression using the current population density and the past rail transit density as of 1980 as instruments.[20] Stata's fractional polynomial routine has chosen the following as the best linear fit:

$$tr_{s,2015} = \theta_0 + \theta_1 tr_{s,1980} + \theta_2 pop_{s,2015}^{0.7} + \theta_3 pop_{s,2015}^{2.0} + \nu_s.$$

We then obtain the estimates of the residual $\hat{\nu}_s$. Note here that we *do not* include choice-specific or household-specific covariates in this first-stage regression because the residual of interest varies only at the district level s. In the second step, we estimate the conditional logit using $\hat{\nu}_s, \hat{\nu}_s^2, \Lambda_{i(j,k)}\hat{\nu}_s$ and $\Lambda_{i(j,k)}\hat{\nu}_s^2$ along with other covariates in the original utility. Note, however, that the first two terms $\hat{\nu}_s$ and $\hat{\nu}_s^2$ are canceled out since they are constant across choice alternatives. There is one remaining issue. We have no *a priori* knowledge on $\Lambda_{i(j,k)}$, and without it, we need to estimate them as choice-specific parameters. This results in estimating 168 additional parameters. Our earlier attempt has resulted in non-convergence. Hence, we have chosen an alternative route. By assumption, choice-specific attributes such as $\mathbf{Z}_j, \mathbf{Z}_k$, and $I(j,k)$ are pre-determined, and thus, their interactions with $\hat{\nu}_s$ should be able to parsimoniously handle this term. Hence, we estimate the second-stage model, interacting $\hat{\nu}_s$ and $\hat{\nu}_s^2$ with these observed choice-specific attributes.

Rental price of car ownership: Studies on the automobile demand estimation are often concerned with the endogeneity of car prices. There may be product attributes consumers see but researchers do not, such

[20] We make sure that all of the households included in the estimation do not own cars sold prior to 1980.

as brand images, styles, and non-price incentives. Since they are demand-shifters, they may as well be correlated with car prices. This concern is less serious in our study because ours is based on household data and car prices are mostly determined at the market level. In addition, we include make, car-type, fuel-type, and used-car dummies to control for unobservable product characteristics. This identification strategy is analogous to Goldberg (1998) and Bento *et al.* (2009). However, individual households also negotiate prices at the dealer level. Hence, there may be some measurement error in our price variable that may be correlated with vehicle attributes at the local level. To take care of the concern, we use *time-varying* car-related tax incentives as exogenous price shifters. Specifically, we use information on purchase year/month to adjust the rental prices of *all* vehicles in each household's choice set. The Japanese government implemented a variety of incentives for eco-friendly vehicles since 2001 [see Konishi and Zhao (2017) for more detail]. This not only gives us exogenous price variation, but also implicitly restrict each household's choice set.

Sample selection: For the second-stage choice of car utilization, we essentially have two identification issues. Both issues are closely related to the endogeneity of p, i.e., the operating cost of vehicle utilization. The first issue concerns the sample selection we discussed in Section III. Because the fuel cost per kilometer is a function of the fuel economy rating of the car chosen, this variable is clearly correlated with unobservable demand for driving distance. To control for this, we use Dahl's control function approach. This approach requires the exclusion restriction: i.e., we need instruments that vary at the household level and affect vehicle purchase decisions, yet do not affect vehicle utilization decisions directly. In our case, this is trivially satisfied. Vehicle utilization in eq. (4) depends only on the attributes of the car that is actually owned, but not those of alternatives, while vehicle ownership choice in eq. (2) depends not only on the attributes of the chosen car but also on those of the other alternatives. Previous studies essentially use the same argument in implementing Dubin-McFadden type correction. The identifying condition is further strengthened by the fact that we use the prices of alternative vehicles actually observed at the time of purchase instead of using contemporaneous values observed today, as discussed above.

Duration of car ownership: The second identification issue for the vehicle utilization regression concerns the duration of car ownership. The problem here is that those who own cars longer tend to be those with low incomes and own cars with low fuel economy ratings (both because cars sold in the past tend to be fuel-inefficient and because fuel-efficient cars tend to be expensive), while at the same time, these households continue to hold cars despite their low incomes precisely because they have high demand for driving. Hence, households who hold the same car for a long time tend to be those with lower incomes and higher costs of vehicle utilization. This results in spurious correlations that bias the parameter estimates in the opposing direction—i.e., negative correlation between net income and VKT and positive correlation between the cost of driving and VKT. Our first-stage model of car ownership allows us to account for the economic margins that affect "whether or not," "how many," and "what type of cars" to own, but not "how long” to own. Naturally, the selection correction terms cannot control for the endogeneity that arises from the duration of ownership. To address this concern, we restrict the observations to those on cars purchased after 2012.

Appendix D. Details for Counterfactual Simulation

This appendix complements Section VII.

D1. Gradating the Amount of the Rebate

Our simulations focus on the economic consequences of a gradient distribution of the carbon dividend based on several criteria: (a) no rebate, (b) flat (or uniform) rebates, (c) income-based rebates, and (d) place-based rebates.

Flat-rebate is a *uniform* lump-sum rebate for all households, including those that do not own a car, and the sum of all households in this rebate is exactly equal to the total tax revenue. Hence, the amount rebated to household i, R_i, is expressed as:

$$R_i = \delta$$

where δ is the average of all households of carbon tax paid.

Income-based allocation scenario determines the amount of rebate according to household income. To investigate the observed changes in the economic consequences of the counterfactual policy of different rebate grading methods, we set a strong gradient as follows:

$$R_i^I = \left(\frac{1}{5}\tau_i^I - 0.1\right)\delta$$

where τ_i^I denotes the ordinal numbers of the income deciles, i.e., $\tau_i^I \in \{1,2,\dots,10\}$. Note that the average of all households in R_i is equal to δ. This formula means that households in the 1st income decile (lowest income) receive almost no rebate, while households in the 10th decile (highest income) receive about twice the δ rebate.

Place-based scenario determines the amount of the rebate based on the household's decile of public transit density, similarly to the income-based scenario. We define

$$R_i^T = \left(2.1 - \frac{1}{5}\tau_i^T\right)\delta$$

where τ_i^T denotes the ordinal numbers of the public transit density deciles. This setup means that households living in the areas with the lowest public transit density (i.e., rural areas, $\tau = 1$) receive a rebate of about twice the δ, while households living in the areas with the highest density (i.e., urban areas, $\tau = 10$) receive almost no rebate.

Table D.1 shows the amount of rebate paid annually to one household under $\delta = 0.67$ (10,000 JPY), assuming an SCC of \$50/ton-CO_2.

Table D.1. Excerpt of Rebate Amount for $\delta = 0.67$ in 10,000 JPY

Public Tansit Density (Deciles)	Income (Deciles)		
	1st (Lowest)	5th	10th (Highest)
Panel A. Flat-Based Recycling			
1st (Lowest)	0.670	0.670	0.670
5th	0.670	0.670	0.670
10th (Highest)	0.670	0.670	0.670
Panel B. Income-Based Recycling			
1st (Lowest)	0.067	0.603	1.273
5th	0.067	0.603	1.273
10th (Highest)	0.067	0.603	1.273
Panel C. Place-Based Recycling			
1st (Lowest)	1.273	1.273	1.273
5th	0.737	0.737	0.737
10th (Highest)	0.067	0.067	0.067

D2. Alternative Scenario: More Aggressive Place-Based Rebates

Our main simulations find that the place-based rebate significantly mitigates welfare losses for the households that would suffer from carbon tax the most, i.e., low-density and low-income households. An equity perspective may provide policy support for a larger rebate for low-density and low-income households. We consider the following graded allocation with a very simple piecewise linear function:

$$R_i^{T2} = \max\{0, (5 - \tau_i^T)\delta\}.$$

This means that households living in the least density areas ($\tau = 1$) receive a rebate of four times δ, households in the 4th decile ($\tau = 4$) receive a rebate equal to δ, and households living in areas denser than the median ($\tau \geq 5$) receive no rebate at all.

Aggressive place-based schemes reduce the rate of reduction of carbon emissions in rural areas, however, they substantially improve welfare losses for low-income households in rural areas. Thus, the social welfare in this scenario is higher than that of the standard place-based scheme.

Figure D.1. Heterogeneous Impacts of Counterfactual Policies:
More Aggressive Place-Based Rebates

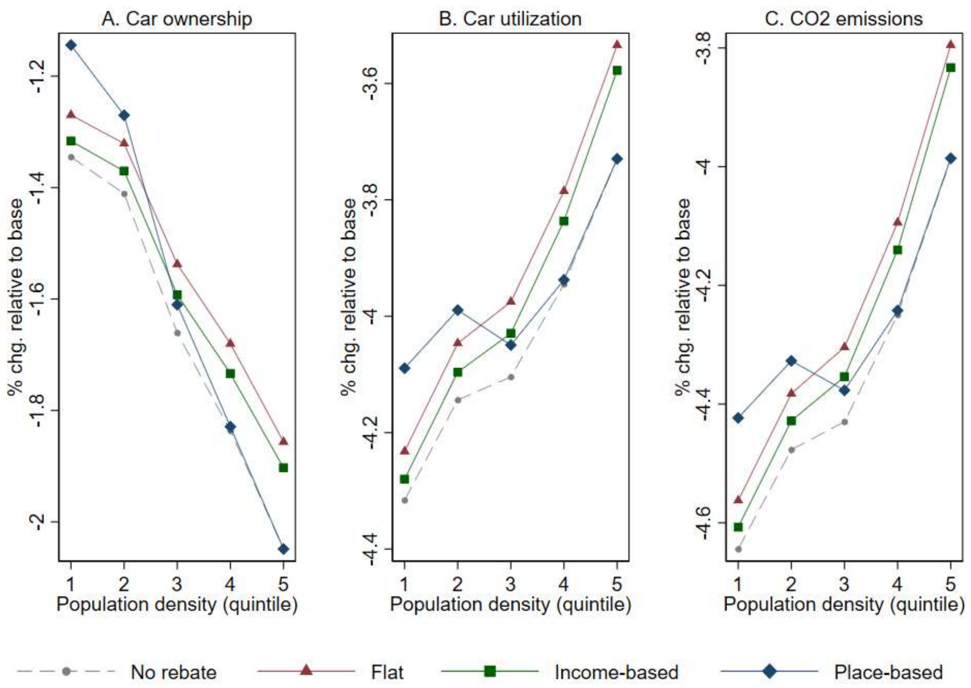


Figure D.2. Welfare Impacts of Counterfactual Policies:
Differences in Welfare Between With-Rebate and Without-Rebate in
More Aggressive Place-Based Rebates

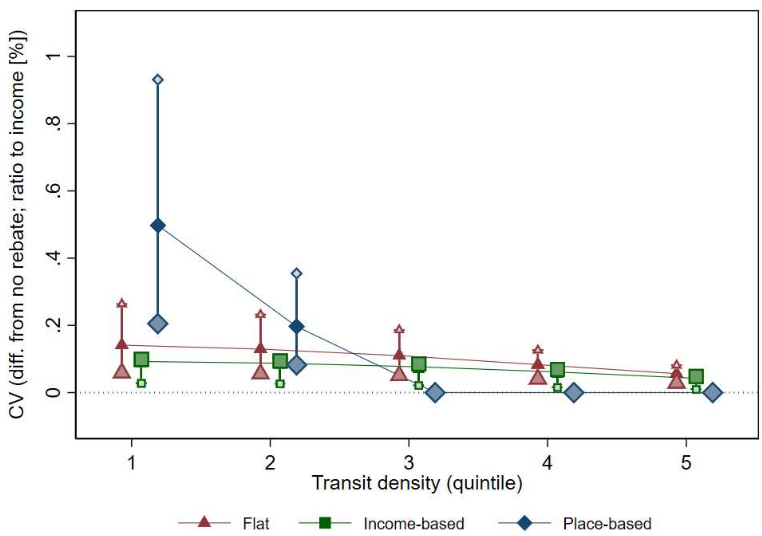


Table D.2. The Overall Average Impacts of Counterfactual Policies:
More Aggressive Place-Based Rebates

Counterfactual Policy	CO_2 Emissions (ton-CO_2/yr)	Chg. in Consumer Welfare (JPY) (a)	Chg. in CO_2 Damages (JPY) (b)	Chg. in Social Welfare (JPY) (a) + (b)	Rebate Amount (JPY)
Carbon Tax with No Rebate	1.357	--	--	--	--
Carbon Tax with Rebates					
Flat-Rebate	1.359	+4,615	-12.1	+4,603	6,733
Income-Based Rebate	1.358	+4,885	-7.2	+4,878	6,733
Place-Based Rebate	1.359	+5,841	-13.0	+5,828	6,733

D3. Alternative Scenario: Social Cost of Carbon of $200/ton-$CO_2$

All of our primary counterfactual policies use $50/ton-$CO_2$ as the social cost of carbon (SCC), but it has recently been pointed out that this value may underestimate the actual social cost. We show the economic impact of using $200/ton-$CO_2$ as the SCC, which some researchers support (e.g., Rennert *et al.*, 2022; EPA, 2023).

Figure D.3, D.4, and Table D.3 show that higher tax rates achieve higher carbon emission reductions, and that the difference between the rebate scenarios is almost negligible compared to the case where the SCC is $50/ton-$CO_2$.

Figure D.3. Heterogeneous Impacts of Counterfactual Policies: SCC value of \$200/ton-CO_2

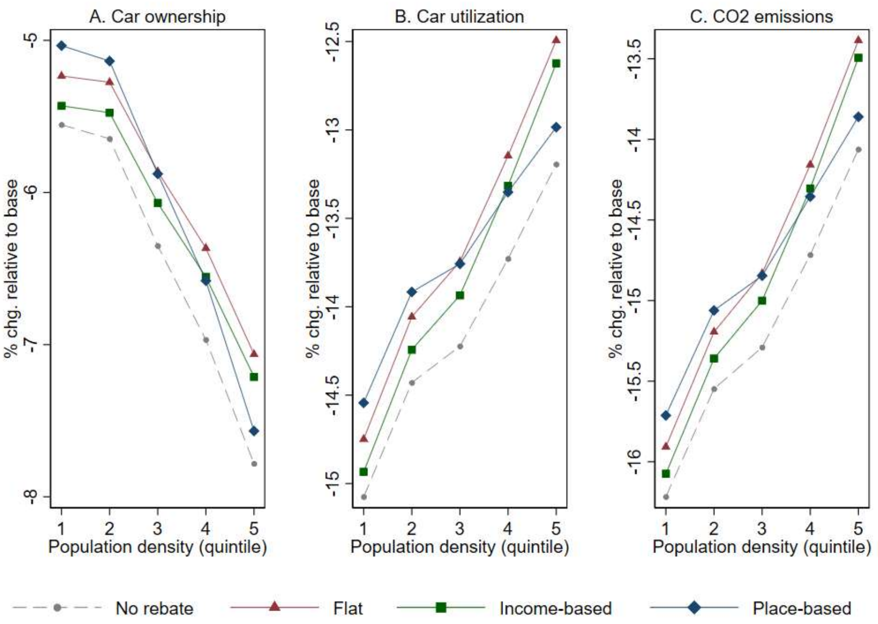


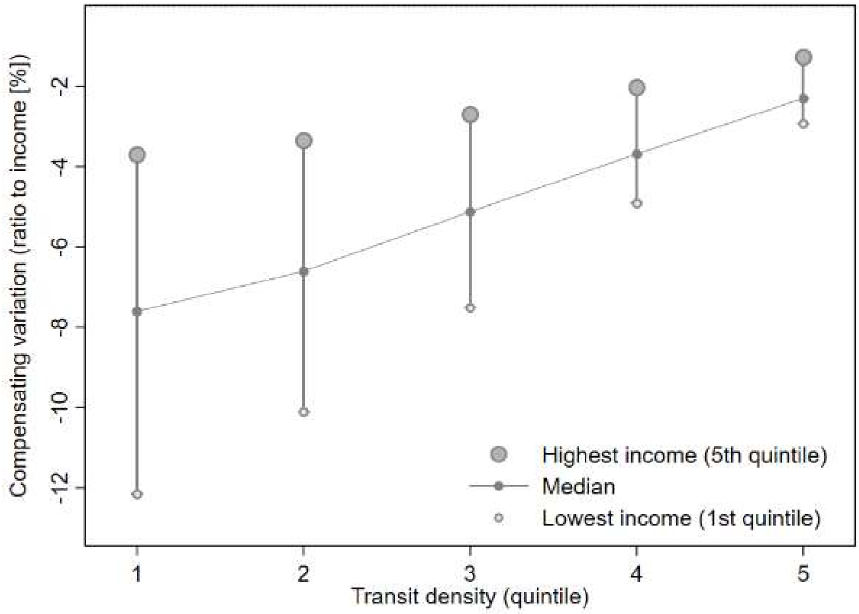
Table D.3. The Overall Average Impacts of Counterfactual Policies:

SCC value of \$200/ton-CO_2

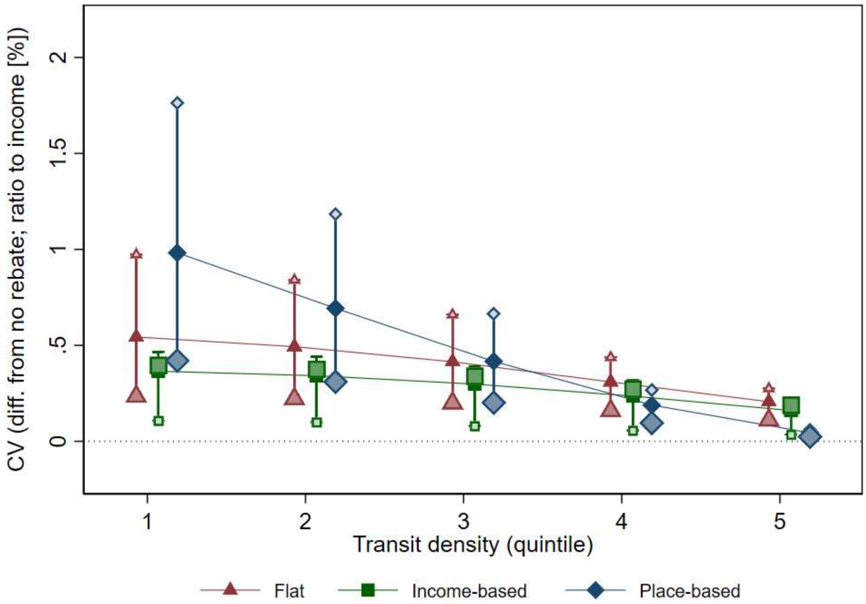
Counterfactual Policy	CO_2 Emissions (ton-CO_2/yr)	Chg. in Consumer Welfare (JPY) (a)	Chg. in CO_2 Damages (JPY) (b)	Chg. in Social Welfare (JPY) (a) + (b)	Rebate Amount (JPY)
Carbon Tax with No Rebate	1.201	--	--	--	--
Carbon Tax with Rebates					
Flat-Rebate	1.206	+17,844	-44.1	+17,799	26,933
Income-Based Rebate	1.204	+19,143	-27.2	+19,116	26,933
Place-Based Rebate	1.207	+20,521	-47.2	+20,474	26,933

Figure D.4. Welfare Impacts of Counterfactual Policies: SCC value of \$200/ton-CO_2

Panel A. Welfare of No Rebate Scenario Relative to No Tax (Status Quo)



Panel B. Differences in Welfare Between With-Rebate and Without-Rebate



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