Dirty Trade: How Global Used Vehicle Trade Mediates Clean Transitions*

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Abstract

Clean vehicle policies can accelerate transitions to greener economies in countries that adopt them, yet displaced used vehicles may enter the global market, with uncertain consequences for emissions and welfare abroad. This paper studies the spillover effects of Japanese Clean Energy Vehicle subsidies from 2013 to 2024 on Uganda, where around 90% of first-time registered passenger vehicles were used imports from Japan. I link Japanese subsidy schedules to data on first-time registrations, prices, and emissions of vehicles in Uganda. Exploiting variation in exposure to subsidies across different vehicles and over time, difference-in-differences estimates suggest that the subsidies decreased prices and increased the number of first-time registered vehicles. The effects were concentrated among vehicles aged 6–13 years, which were younger and generally less emissions-intensive than the average first-time registered vehicle in Uganda. To quantify the equilibrium effects of the subsidies on total emissions and welfare, I estimate a model of vehicle demand and supply in Uganda with endogenous inflows and scrappage. Simulations show that the subsidies increase total emissions, as fleet expansion outweighs the reduction in average emissions per kilometer. Nonetheless, gains in consumer surplus lead to an increase in welfare. The subsidies also change the trade-off associated with age-based import restrictions in Uganda. Tightening the import age limit from 15 to 13 years, as recently proposed, lowers total emissions at the cost of consumer surplus. Through lower prices of younger vehicles, the subsidies decrease the resulting emissions savings, as the smaller reduction in the fleet size dominates the larger reduction in average emissions per kilometer. Losses in consumer surplus also decrease, but to a lesser extent. Consequently, the tighter limit reduces welfare under the subsidies, whereas it would have increased welfare in their absence.

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1 Introduction

Many developing countries depend heavily on imported used vehicles. In 2018, an estimated 70% of emerging and developing economies imported more used vehicles than new ones (World Bank, 2022b). Much of this trade originates in a few major exporting economies. Between 2015 and 2018, the three largest exporters of used vehicles, the European Union, Japan, and the United States, collectively exported 14 million used light-duty vehicles worldwide, approximately 70% of which went to developing countries (United Nations Environment Programme, 2020).

The cross-border flows have long raised concerns that displaced vehicles from clean vehicle policies in exporting countries flow into developing countries rather than being retired, potentially increasing emissions in importing countries.[1] Such concerns are especially important given that many importing countries face severe air pollution (Rentschler and Leonova, 2023), with road transport often being a leading contributor (World Bank, 2025). However, the environmental consequences of the flows are ambiguous. On the one hand, increased imports can expand the fleet in importing countries, raising total emissions. On the other hand, vehicles displaced from exporting countries may be cleaner than those already operating in importing countries, shifting the fleet toward cleaner vehicles and reducing average emissions per kilometer. The net effect on emissions depends on the relative strength of the *market expansion effect* and *composition effect*. Moreover, consumers can benefit from access to more and potentially higher-quality imports, increasing consumer surplus. Welfare, defined as consumer surplus net of emissions damages, can therefore rise even if emissions increase.

The spillover effects of foreign clean vehicle policies also matter for designing import restrictions in importing countries. Because younger vehicles are generally less emissions-intensive, many importing countries have implemented age-based import restrictions to reduce emissions from road transport. For instance, 67 of the 146 importing countries surveyed in United Nations Environment Programme (2020) imposed maximum import age limits, most of them between 3 and 15 years. However, these restrictions can also raise prices and limit consumer access, so regulators face a trade-off between reductions in emissions damages and losses in consumer surplus. Through their effects on the size and composition of the fleet, foreign clean vehicle policies can change both sides of this trade-off for a given restriction. The appropriate choice of import restrictions may thus depend on clean vehicle policies set abroad.

In this paper, I examine two questions. How did clean vehicle policies in a major exporting country affect emissions and welfare in an import-dependent country? How should such an importing country design its import restrictions in response? I use Japan's Clean Energy Vehicle (CEV) subsidies from 2013 to 2024 and Uganda as the setting. During the period, 91% of first-time registered passenger vehicles in Uganda were used imports from Japan. Local air pollution is a severe problem in the country, with particulate matter concentrations far exceeding WHO guidelines and road transport being an important source of emissions (Crowe et al., 2025). Uganda

[1] For example, Japan's 2003 Automobile Recycling Law has been described as a "used-vehicle-export-promotion law," and more recently EV subsidies in developed countries have been described as creating "floods" of used vehicles into developing countries. See, for example, https://autorecyclingworld.com/the-japanese-automobile-recycling-system-is-it-a-success/ and https://www.vox.com/future-perfect/369695/used-cars-electric-vehicles-buy-exports, last accessed October 2026.

has imposed age-based import restrictions, including a maximum import age limit of 15 years since 2018. More recently, it proposed tightening the limit to 13 years. In Japan, the CEV subsidies were substantial, reaching more than 30% of the manufacturer's suggested retail price (MSRP), and varied considerably across vehicle variants and fiscal years. Though they applied only to new vehicles registered in Japan, the subsidies could encourage existing vehicle owners to replace their cars, increasing the supply of used vehicles available for export and lowering their prices, potentially unevenly across ages.

Two main challenges arise in answering the questions. First, measuring the international spillovers requires linking Japanese subsidies to the characteristics, prices, and quantities of vehicles entering Uganda. However, this information is scattered across sources from both countries, with no centralized database that contains it all. Second, the effects of international spillovers on emissions and overall welfare, as well as the implications for designing import restrictions, depend not only on which and how many vehicles are imported but also on how long imported vehicles stay on the road. In addition, Japanese subsidies and Uganda's import restrictions can change when existing vehicles are scrapped. Lower prices under the Japanese subsidies can accelerate their scrappage, while higher prices under a tighter age limit can delay it. In both cases, changes in scrappage offset part of the changes in imports. However, unlike first-time registrations, there is no comprehensive database on scrappage in Uganda, a data limitation also encountered in many other countries (e.g., Kebede (2021)).

To address these challenges, I assemble a novel database linking multiple datasets based on detailed vehicle characteristics and time. I compile CEV subsidy schedules for individual vehicle variants from online Japanese government documents. For Uganda, I obtain comprehensive vehicle-level first-time registration records for January 2013 to June 2024, as well as vehicle-level import and individual-level income tax records, from the Uganda Revenue Authority (URA). I collect prices from archived listings on online platforms selling cars in Uganda and emissions data from Japanese automobile databases. Complementing these sources, data from Crowe et al. (2025) contain on-road emissions measurements and ages of randomly selected passenger vehicles in Kampala in July 2024. Besides real-world emissions, this dataset provides a snapshot of the fleet's age distribution. Comparing the inflows from first-time registrations, drawn from Mutenyo et al. (2015) for 2000–2012 and the URA for 2013–2024, with what remains in this snapshot allows me to infer scrappage without direct data on it.

Using these data, I first estimate the effects of Japanese subsidies on the number and average price of first-time registered vehicles in Uganda with difference-in-differences (DiD) regressions. Existing literature documents strong preferences for particular makes and substantial within-make substitution in automobile purchases, including in Japan, with explanations such as lower uncertainty about the quality of particular makes and established relationships with their affiliated dealerships (e.g., Mannering and Winston (1991), Kato (2021)). I therefore measure exposure to subsidies with the average Japanese subsidy among variants of the same make in each fiscal year. Identification relies on conditional parallel trends in the absence of Japanese subsidies across makes with different exposure to subsidies, a plausible assumption given that I find no statistically significant effects of future subsidies on current outcomes and that Japanese subsidies are unlikely

to respond to demand conditions specific to Uganda. The estimates show that an additional 1,000 USD in the annual average subsidy for a given make increases its first-time registrations in Uganda by 5.76% and decreases the average price by 2.61%. The effects are largest in magnitude among cars aged 6–13 years, which are relatively young and generally less emissions-intensive compared to existing vehicles in Uganda. In robustness checks, I additionally allow for cross-make substitution in both Japan and Uganda and find that the estimated effects of subsidies on cars of the same make remain stable, while the estimated effects of subsidies on cars of other makes within the same segment are statistically insignificant, lending support to the choice of make-level exposure to subsidies.

I then develop a model of vehicle demand and supply with endogenous inflows and scrappage in Uganda to estimate the equilibrium effects of Japanese subsidies on emissions and welfare, and to evaluate alternative age-based import restrictions. It builds on the framework of static demand and dynamic fleet evolution in Jacobsen et al. (2023). In each period, consumers with existing vehicles scrap them if their repair costs, drawn from age-dependent distributions, exceed their prices. Consumers then choose among the surviving vehicles and those available for import based on user costs, which equal prices plus discounted expected repair costs minus discounted expected resale values. Their choices follow a nested logit model with income-dependent preferences and makes as nests. Prices of products with positive imports equal landed prices. Prices of other products adjust to equate demand with the surviving stock, which itself depends on prices through scrappage. The fleet evolves over time through inflows, aging, and scrappage.

While Jacobsen et al. (2023) calibrate their model, I estimate my model using both aggregate and micro moments. To estimate heterogeneous consumer preferences, I follow the differentiated-product demand estimation tradition from Berry et al. (1995), incorporating income-related micro moments (e.g., Petrin (2002), Berry et al. (2004), Berry and Haile (2024)). Japanese subsidies serve as instruments for prices in Uganda. To estimate age-specific repair cost distributions, I match the implied age distribution of the surviving stock in July 2024 with the age distribution observed among passenger vehicles randomly sampled by Crowe et al. (2025) in Kampala for on-road emissions tests in the same month. The implied age distribution is constructed from historical first-time registrations, accounting for aging and implied scrappage over time.

Equipped with the estimated model, I compare outcomes with and without Japanese subsidies under the existing 15-year import age limit in Uganda, constructing landed prices of first-time registered cars absent subsidies with the estimated age-specific effects from the main DiD price regression. The simulated demand responses to Japanese subsidies in first-time registrations across ages closely match the DiD estimates, supporting the choice of make-level exposure to subsidies in the DiD regressions. In addition, the simulations show that Japanese subsidies expand the fleet in Uganda despite increased scrappage and shift its composition toward less emissions-intensive vehicles. With subsidies, the fleet is 4.65% larger, and average emissions per kilometer are lower by 1.24% for CO_2, 2.29% for NO_x, and 2.05% for particulate number (PN) in the last simulated year. However, the subsidies increase total emissions of CO_2, NO_x, and PN by 3.95%, 2.85%, and 3.11% in the same year, as the market expansion effect outweighs the composition effect. On the other hand, the subsidies also increase consumer surplus through more and cheaper cars. Overall, the

subsidies increase welfare in Uganda.

Finally, I apply the estimated model to evaluate the recent proposal to tighten its import age limit from 15 to 13 years in Uganda. The tighter limit shifts the fleet toward less emissions-intensive vehicles while reducing its size, lowering emissions damages at the cost of consumer surplus. Japanese subsidies change this trade-off. Compared with a scenario in which Japanese subsidies are absent, the smaller reduction in the fleet size dominates the larger reduction in average emissions per kilometer, resulting in smaller emissions savings relative to the losses in consumer surplus. In the end, tightening the limit reduces welfare under the existing Japanese subsidies, whereas it would have increased welfare in their absence.

Related literature There is a large literature that documents substantial environmental damages from transport emissions (e.g., Knittel et al. (2016)) and estimates the environmental effects of various transportation policies. Examples include clean vehicle policies (e.g., Goldberg (1998), Davis (2008), Barahona et al. (2020), Reynaert (2021), Xing et al. (2021), Gillingham et al. (2022), Jacobsen et al. (2023), Allcott et al. (2024), Wang and Xing (2025), Armitage and Pinter (2026), Barwick et al. (2026), Ito et al. (2026)), as well as public transit investments (e.g., Chen and Whalley (2012), Gendron-Carrier et al. (2022), Bel and Holst (2018)). While most studies in the literature only consider the effects within countries, Ito et al. (2026) is a rare exception showing that there are positive global environmental spillovers of fuel economy standards through shared new car designs across countries. I instead consider global spillovers through secondary markets. In contrast to Ito et al. (2026), I show that ignoring international spillovers through secondary markets can overstate the global environmental benefits of clean vehicle policies in exporting countries.

Relatedly, existing papers such as Tanaka et al. (2022), Atalar et al. (2024), and Xiang (2025) also estimate the global spillovers of incomplete environmental regulations, albeit in other industries. Consistent with the pollution haven hypothesis, spillovers in their cases operate through dirty production relocation to countries with weaker environmental regulations, under which the importers bear the negative environmental spillovers, at least in the short run, while not necessarily being able to consume the relocated output. In my case, however, the environmental spillovers depend on the emissions gap between induced used vehicle imports and the existing fleet in the importing country, and their directions are thus uncertain ex ante. Moreover, consumers in the importing countries directly benefit from increased access to vehicles, further complicating the overall welfare implications.

This paper also adds to the literature on the global trade in used vehicles and the effects of import restrictions. Papers in this literature show that liberalizing trade in used vehicles leads to increases in imports and total emissions in the importing countries (e.g., Clerides (2008) and Davis and Kahn (2010)), but properly designed import restrictions can mitigate the negative environmental effects (e.g., Forster and Nakyambadde (2021)). Unlike existing studies in this literature, I account for the foreign policy environment. I show that clean vehicle policies in exporting countries can change the trade-off between emissions reductions and losses in consumer surplus from import restrictions in importing countries, potentially changing the optimal choice of import restrictions. I also endogenize scrappage when estimating the effects of import restrictions, rather than taking

it as exogenous. Endogenous scrappage matters because import restrictions can raise the prices of previously imported vehicles, delaying their scrappage and thus offsetting some of the emissions reductions from reduced imports.

Outline Section 2 provides the institutional background, and Section 3 describes the data. Section 4 presents difference-in-differences estimates of the effects of Japanese subsidies on the number and average price of first-time registered vehicles in Uganda. Section 5 develops the equilibrium model. Section 6 describes its estimation and presents the parameter estimates. Section 7 estimates the effects of Japanese subsidies and the tighter import age limit on fleet dynamics and welfare in Uganda. Section 8 concludes.

2 Institutional Background

2.1 Car Markets in Uganda

Like many low-income countries, Uganda has little domestic vehicle production capacity and relies almost entirely on used vehicle imports.[2] Based on the official import and registration records from the Uganda Revenue Authority (URA), around 99.2% of first-time registered light-duty passenger vehicles between January 2013 and June 2024 were used vehicles,[3] 91.6% of which were imported directly from Japan. The average age among first-time registered light-duty passenger vehicles was more than 15 years.

Road transport is a major contributor to urban air pollution in the country, and Uganda has adopted age-based import restrictions to reduce emissions from this sector. For example, studies estimate that road transport accounts for up to 24% of $PM_{2.5}$ pollution and 60% of NO_2 pollution in Kampala (Crowe et al., 2025). Since older vehicles are generally more emissions-intensive due to factors such as outdated and deteriorating technology (e.g., International Energy Agency (2019), Jacobsen et al. (2023), Ito et al. (2026)), age-based import restrictions can shift the composition of inflows toward less emissions-intensive vehicles. However, such restrictions can also limit consumer access. This creates a trade-off that Uganda considers when designing import restrictions.[4] In an effort to balance these competing objectives, Uganda introduced a 10% environmental levy on imported used vehicles older than 7 years in 2006, assessed as a percentage of their customs value, and increased it multiple times in subsequent years. In 2018, Uganda introduced a maximum import age of 15 years, prohibiting imports of older vehicles. Table 1 summarizes the evolution

[2] In 2019, Kiira Motors Corporation, a state-owned enterprise in Uganda, did establish a local electric vehicle assembly plant. However, it had not started mass production and had produced fewer than 30 vehicles by 2025. See https://sti.go.ug/wp-content/uploads/2025/06/E-Mobility-Outlook-Report-2024.pdf for detailed statistics, last accessed October 2026.

[3] I count vehicles as used if they were first registered in Uganda at least one calendar year after their manufacture. Requiring a gap of more than one, two, or three years yields shares of 98.0%, 97.5%, and 97.1%, respectively.

[4] See https://hellouganda.com/shout/item/47-why-you-pay-more-taxes-on-newer-used-cars.html and https://bills.parliament.ug/attachments/FPED3-18-Report%20on%20the%20Traffic%20and%20Road%20Safety%20Act%201998%20%28Amendment%29%20Bill%2C%202018.pdf for details, last accessed October 2026.

of the import restrictions. In March 2026, Uganda proposed lowering the age limit to 13 years.[5] The proposal was subsequently withdrawn in April 2026 amid concerns that its environmental benefits might not justify the potential costs to consumers.[6]

	Environmental levy (%)			
	2006	2009	2015	2018
0-5	0	0	0	0
6-7	0	0	35	0
8-9	10	20	35	50
10-15	10	20	50	50
16+	10	20	50	Banned

Notes: Environmental levies are charged as a share of customs value.

Table 1: The import restrictions in Uganda

Besides domestic import restrictions, Uganda's strong reliance on used vehicle imports exposes it to foreign clean vehicle policies, which can in turn change the consequences of its import restrictions. In particular, Japanese clean vehicle subsidies can change used vehicle prices in Uganda, even when the subsidies are only for eligible new vehicle purchases in Japan. The mechanism is that subsidies incentivize existing owners in Japan to replace their current vehicles with subsidized new vehicles. Other existing owners in turn purchase some of those displaced vehicles and sell their current vehicles. Subsidies can therefore initiate chains of replacement that increase the supply and lower the prices of unsubsidized used vehicles, especially for those that share characteristics, such as the make, and are more substitutable with the subsidized new vehicles. Given that subsidized makes represent 28% of imported makes and 98% of import volume, as computed with data described in Section 3, the subsidies are particularly relevant to Uganda. Lower prices for used vehicles from Japan can increase demand for these vehicles in Uganda and thereby increase used vehicle imports, a market expansion effect. Changes in relative prices can also induce substitution across vehicles and change the composition of vehicles imported into Uganda, a composition effect. Japanese subsidies can thus change the effects from Uganda's age-based import restrictions on the number and composition of imports and, consequently, the trade-off between emissions reductions and costs to consumers associated with the restrictions.

In fact, as pointed out in earlier work (e.g., United Nations Environment Programme (2020) and Forster and Nakyambadde (2021)), the import restrictions in Uganda are part of a broader trend in import-dependent developing countries that adopted age-based restrictions to improve the environmental performance of imported vehicles. Kenya, for example, has had an age limit of 8 years old since the 2000s.[7] Uganda thus provides an ideal setting for studying the interactions between

[5] See, for example, https://dailyexpress.co.ug/2026/03/27/govt-proposes-ban-on-importation-of-cars-older-than-13-years/ for a news report about this proposal, last accessed October 2026.

[6] See https://bills.parliament.ug/attachments/FPED3-26-Report%20on%20the%20Traffic%20and%20Road%20Safety%20%28Amendment%29%20Bill%2C%202026%20%20%28Including%20Minority%20Report%29.pdf and https://www.bills.parliament.ug/user_bill_stage.php?billid=575 for the parliamentary committee's assessment of the proposal and confirmation of its withdrawal, last accessed October 2026.

[7] See https://www.kra.go.ke/individual/importing/learn-about-importation/procedures-for-motor-veh

clean vehicle policies in a major exporting country and import restrictions in an import-dependent country, with broader lessons for designing import policies amid international spillovers.

2.2 Japanese Clean Vehicle Subsidies

The purchase incentives for clean vehicles in Japan date back at least to 1996, when the Ministry of International Trade and Industry (MITI) introduced subsidies for new electric vehicles. In 1998, MITI expanded the program into the Clean Energy Vehicle (CEV) Introduction Project, which has since subsidized a broader range of low-emission vehicles, including hybrid, natural-gas, fuel-cell, and clean-diesel vehicles.

For each fiscal year from April to the following March, the MITI, or later its successor, the Ministry of Economy, Trade and Industry (METI), establishes a formula for calculating subsidies primarily based on individual vehicle characteristics,[8] and publishes it together with the application guidelines. For example, in FY2016, subsidies for electric and plug-in hybrid vehicles were calculated as JPY 11,000 per kWh of battery capacity, up to a maximum of JPY 600,000.[9] The manufacturers then submit individual vehicle variants to the program's implementing organization, the Next Generation Vehicle Promotion Center (NeV), for evaluation. Based on the formula and the submitted characteristics, the center determines and publishes the list of eligible variants and their corresponding subsidy amounts. Purchasers of eligible new vehicles can apply to NeV for the corresponding subsidies, subject to the program's registration and application requirements.[10]

Because the formula depends on detailed characteristics and is revised over time, the subsidy assigned to vehicles with the same make and model can change considerably across fiscal years. In many cases, subsidy amounts were also substantial. For example, the subsidy for a Nissan Leaf S variant was 780,000 JPY in 2013, 400,000 JPY in 2019, and 786,000 JPY in 2024, equivalent to 24%, 13%, and 26% of the contemporaneous manufacturer's suggested retail price in those years. Consequently, there is substantial variation in subsidies both across vehicles and over time, which I exploit in my empirical analysis.

3 Data

3.1 First-Time Registrations

I obtain comprehensive vehicle-level records of first-time registrations in Uganda between January 2013 and June 2024 from the URA's e-Tax database.[11] For each vehicle, the records report the date

icle for details, last accessed October 2026.

[8] Beginning in FY2024, the formula also incorporates manufacturers' efforts to expand charging infrastructure, provide after-sales services, and support disaster preparedness, among other factors. See https://www.enecho.meti.go.jp/en/category/special/article/detail_199.html for details, last accessed October 2026.

[9] See https://www.cev-pc.or.jp/notice/pdf/20160420_cev_oshirase.pdf for details, last accessed October 2026.

[10] In some fiscal years, supplementary budgets provided additional funding for subsidies. The subsidy schedules associated with the supplementary budgets could differ from, though were highly correlated with, the initial schedules. Throughout the paper, I measure subsidies using the initial schedule for each fiscal year.

[11] The database also contains some records on changes of ownership after first-time registrations in Uganda. However, as documented in Forster and Nakyambadde (2021), such records are suspiciously rare.

of the first registration, tax identification number (TIN) of the registrant, chassis number, make, model, year of manufacture, and other detailed characteristics. I link these records to vehicle-level import records from the URA's Automated System for Customs Data (ASYCUDA) database using chassis numbers. The matching rate is 97%. The import records provide additional information on the country of export, customs value, and taxes and fees collected upon import. Restricting the sample to light-duty passenger vehicles with matched import records yields 269,653 first-time registrations. Table 2 describes the five most common makes, accounting for 93% of the vehicles in the sample. It shows that Uganda strongly depends on old exports from Japan, even for non-Japanese makes such as Mercedes-Benz.

	Number of first-time registrations		
Make	Total	From Japan	Mean age
Toyota	210,903	198,212	15.92
Subaru	19,413	19,046	13.82
Mercedes-Benz	7,467	4,707	13.93
Mitsubishi	7,127	6,595	15.37
Nissan	6,532	5,646	13.80

Notes: The statistics are based on first-time registration records from January 2013 through June 2024. Mean age is the average of the year registered minus the year manufactured.

Table 2: Top five makes among first-time registered vehicles in Uganda

To obtain information on registrants' annual incomes in the year of registration, I further link the registration records to individual-level monthly tax records from the URA's Pay As You Earn (PAYE) database in the same period using registrants' TINs and years of registration. I compute the annual income as the sum of monthly gross earnings across all employers for each individual.[12] Because the database covers only employees at tax-registered firms, the matching rate is relatively low, at 37%.[13] To assess the representativeness of the annual income distribution from the PAYE for potential car owners, I compare the distribution from PAYE in 2019 with that from the nationally representative 2019/20 Uganda National Panel Survey (UNPS).[14] Figure A6 shows that the distribution from the PAYE first-order stochastically dominates that from the UNPS. However, the two distributions are comparable among relatively rich individuals who are most

[12]Throughout the analysis, I express all monetary amounts in 2013 USD by deflating nominal amounts in their original currencies to 2013 prices using country-specific consumer price indices (CPIs), and then converting them to USD using the corresponding average exchange rates in 2013. The CPIs and exchange rates are from the World Bank's World Development Indicators. See https://databank.worldbank.org/source/world-development-indicators/Series/FP.CPI.TOTL for CPIs and https://databank.worldbank.org/metadataglossary/world-development-indicators/series/PA.NUS.FCRF for exchange rates, last accessed October 2026.

[13]In comparison, the Uganda Bureau of Statistics (UBOS) reports that only 8.1% of employment in Uganda was formal in 2021, where formal employment is defined based on access to social protection and employment benefits. See https://www.ubos.org/wp-content/uploads/publications/11_2022NLFS_2021_main_report.pdf for details, last accessed October 2026.

[14]The Uganda Bureau of Statistics (UBOS) conducted UNPS between March 30, 2019 and February 29, 2020, collecting information on income earned over the preceding 12 months. I construct each individual's annual income in UNPS as the sum of wages, non-agricultural self-employment income, and agricultural income. The distribution from the PAYE is relatively stable across neighboring years, so the choice of 2019 does not materially influence the comparison.

relevant to car markets. For example, Figure A7 shows that the two distributions are comparable conditional on annual incomes exceeding 15 million UGX (equivalent to 5,798 USD at the 2013 exchange rate). In Section 6, I thus use the UNPS to define potential car buyers and PAYE data to construct income-related micro moments and income distributions.

For historical inflows, I draw on comprehensive vehicle-level first-time registration records for 2000–2012 from Mutenyo et al. (2015), who originally source from the URA and Ministry of Works and Transport (MoWT). I similarly retain only light-duty passenger vehicles. Table A1 summarizes the five most common makes, showing substantial historical inflows that had a similar make composition but were, on average, much younger at first registration than those in the 2013–2024 sample.

3.2 Prices

I compile domestic prices from archived webpages of four online platforms where dealers and/or private owners list vehicles for sale in Uganda. The listings include both newly imported vehicles and vehicles already in the domestic stock. Table A2 reports the number of listings collected from each platform and the years in which the listings were archived. For each listing, I collect the date archived, date listed, make, model, year manufactured, mileage, and price. I date each listing with the date posted whenever available and date archived otherwise.

For each make, model, year manufactured, and quarter, I compute the average price among the listings dated to that quarter. Since the year manufactured and the quarter together determine the age, this yields a price for each make, model, and age in each quarter. I define each product as a make–model–age combination. I assume that vehicles of the same product are perfect substitutes sharing a common domestic price,[15] which I measure with the average listed price.

Given that Uganda is a small importer relative to the Japanese used-vehicle export market,[16] I treat products with positive first-time registrations as importable with perfectly elastic foreign supply, such that the no-arbitrage condition between imports and domestic stocks equates their domestic prices with their landed prices. The observed domestic prices of importable products therefore measure their landed prices. Landed prices include import costs, local costs, and possibly markups. Import costs, observed in the import records from the URA, consist of customs values plus taxes and fees collected upon import, while local costs include those associated with inland transportation, inventory holding, and distribution.[17] For products without first-time registrations, predominantly those older than the import age limit, domestic prices instead adjust to equate domestic demand with domestic stocks. Section 5 formalizes this structure.

Because listing coverage is substantially more complete and stable from 2019 onward (Figure

[15] This is consistent with common practice in Uganda's used-vehicle markets, where dealers and media typically quote prices for each make, model, and year manufactured. See, for example, https://www.monitor.co.ug/uganda/business/auto/cars-you-can-get-at-shs15m-and-below-1559964, last accessed November 2026.

[16] For example, Uganda accounted for only 1.9% of used-vehicle exports from Japan in terms of volume in 2023, ranking 14th among destination countries. See https://jumv.net/basic_knowledge_usedcar_export/export_statistics/statistics-by-year?year_from=2023 for detailed statistics, last accessed October 2026.

[17] For example, see https://www.monitor.co.ug/uganda/business/commodities/prices-of-used-motor-vehicles-increase-3870590 for inland transportation costs and https://www.monitor.co.ug/uganda/business/auto/different-ways-of-buying-a-car-1643742 for storage costs, last accessed October 2026.

A4), I use only prices from 2019 onward to estimate the effects of Japanese subsidies on prices in Section 4. Figure A8 compares domestic prices with average import costs in each quarter for products with first-time registrations. It shows that domestic prices generally increase with import costs and mostly exceed them, with a regression slope of 1.30 and an intercept of 2.5 thousand USD. The gap between the two is consistent with the local costs and potential markups that, together with import costs, constitute the landed prices of importable products. Table A3 further shows that the difference in log import costs between cars with and without matched domestic prices becomes small and statistically insignificant after including the controls used in the price regressions in Section 4.2, supporting the plausibility of domestic prices being missing at random conditional on these controls. I therefore estimate the effects of Japanese subsidies on prices in Section 4.2 using only observed prices.

For structural estimation in Section 6, I similarly restrict the markets to 2019 onward. Recovering the initial stock in 2019 still requires historical domestic prices for vehicles registered before 2019. I construct quarterly domestic prices at the make-model-age level for vehicles first registered in Uganda between 2000 and June 2024, covering each year from their first registration onward. I use average listed prices where available and impute missing prices using hedonic price regressions that account for the effects of Japanese subsidies. I then average quarterly prices to construct annual prices. Appendix A.3 provides details on the imputation procedure.

3.3 Emissions

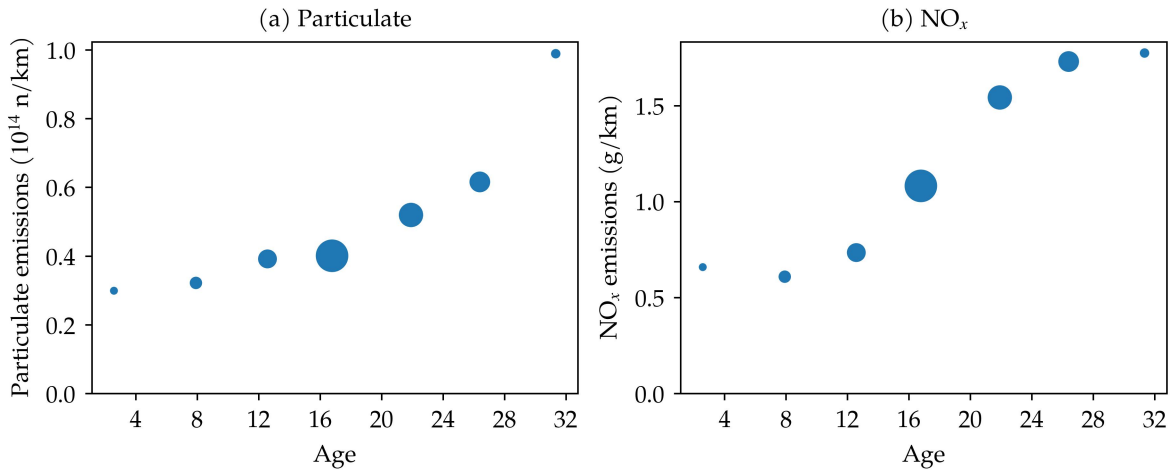
I collect emissions per km traveled of new vehicles from Japanese sources. For each year between 2004 and 2024, I collect the emissions certification code and CO_2 emissions per km traveled for each vehicle variant sold as a new vehicle from the official website of the Ministry of Land, Infrastructure, Transport and Tourism (MLIT). Since the MLIT does not systematically publish this information before 2004, I also collect the emissions certification code and CO_2 emissions from online catalogs of variants ever sold in Japan since 1985 from Gazoo.[18] The certification code identifies the applicable local pollutant emissions standard, the level at which the variant was certified below the regulatory limits, and its fuel and emissions-control technology. I use these codes to construct NO_x and particulate emissions per kilometer for each variant when new. Appendices A.1 and A.2 detail the construction of these emissions measures, as well as the standardization of CO_2, NO_x, and particulate emissions across different test cycles. In general, younger vehicles are less emissions intensive, reflecting differences in technologies at the time of manufacture. Figure A5 illustrates this pattern for CO_2 emissions.

For each vehicle in the sample, I match it to the average emissions among variants with the same make, model, and year, where the year corresponds to the year manufactured in the administrative records and the year sold in the emissions data. I use Gazoo first and MLIT whenever Gazoo is unavailable. The matching rate is 91% for CO_2 emissions and 94% for NO_x and particulate

[18] Unlike the MLIT, Gazoo reports fuel economy in kilometers per liter of fuel but not grams CO_2 per km traveled. I thus divide the corresponding fuel emission factor (grams of CO_2 emitted per liter of fuel) by each reported fuel economy to have CO_2 emissions in grams per kilometer traveled. The fuel emission factors are from the U.S. Environmental Protection Agency. See https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle for details, last accessed October 2026.

emissions among all first-time registered vehicles in the sample between January 2000 and June 2024.[19] I impute missing emissions from the trends in emissions across years for the same make and model or, when a make and model is never observed, the most narrowly defined comparable group. Appendices A.1 and A.2 document the imputation procedure in detail.

Unlike CO_2 emissions, local air pollutant emissions increase with age as emissions control equipment deteriorates (e.g., Jacobsen et al. (2023)). In Kampala, Crowe et al. (2025) also find evidence for malfunctioning or removed emissions-control equipment amid limited enforcement of emissions standards, leading to excessive local air pollutant emissions. To account for these factors, I draw on data from Crowe et al. (2025), who measured on-road emissions from 3,283 randomly sampled passenger cars in Kampala in July 2024. Figure 1 shows that older vehicles in this sample generally emit more particulate matter and NO_x per kilometer traveled, similar to the pattern for CO_2 emissions in Figure A5. In this case, however, the pattern also reflects age-related deterioration of emissions-control equipment. I accordingly calibrate age-related adjustments to emissions of new vehicles so that the average emissions of the fleet in July 2024 match the observed averages by pollutant and age group. The fleet in July 2024 is derived from the estimated model in Section 6. Appendix A.2 details the calibration.



Notes: The figure plots the mean age against the mean particulate emissions (panel a) and the mean NO_x emissions (panel b) per km traveled for passenger vehicles in seven age groups: 0–4, 5–9, 10–14, 15–19, 20–24, 25–29, and 30+ years. The means are calculated using the 3,283 passenger vehicles sampled for on-road emissions testing in Crowe et al. (2025). Dot sizes are proportional to the number of sampled vehicles in each group.

Figure 1: Particulate and NO_x emissions

3.4 Subsidies

Finally, I compile Japanese Clean Energy Vehicle (CEV) subsidy schedules for fiscal years 2011–2024 from publicly available online documents.[20] For each fiscal year, I collect the list of eligible

[19] The difference in the matching rates is from variants whose catalogs on Gazoo report the emissions certification code but not fuel economy.

[20] The FY2012 schedule is needed to measure exposure to subsidies in the first quarter of 2013, which falls in Japan's FY2012, while the FY2011 schedule is needed to construct the lag.

light-duty passenger vehicle variants and their corresponding subsidy amounts. The resulting dataset contains subsidies for 4,370 variant-year observations. Figure A10 plots the mean and standard deviation of subsidies across eligible variants in each fiscal year, showing substantial variation both across variants and over time.

I match the Japanese subsidy schedules to the Ugandan first-time registration records using detailed vehicle characteristics, such as make, according to the definition of exposure to subsidies in each specification. I also match Japanese fiscal years to the corresponding quarters of first registration in Uganda. The linked data show that among makes observed in Uganda, 28% were associated with at least one subsidized vehicle variant in Japan, accounting for 98% of first-time registrations in the sample. The average annual subsidy across makes and fiscal years was 3,824 USD, with a standard deviation of 2,974 USD.

4 Difference-in-Differences Estimates

In this section, I provide reduced-form evidence on the spillover effects of Japanese CEV subsidies. Using difference-in-differences (DiD) regressions, I estimate their effects on the number, composition, and prices of first-time registered vehicles in Uganda.

4.1 Effects on the Number and Composition of First-Time Registered Vehicles

I start from examining whether subsidies in Japan change the number and composition of first-time registered vehicles in Uganda with Poisson pseudo-maximum likelihood (PPML) regressions and quarterly data from January 2013 through June 2024. Doing so requires defining the set of used vehicles whose demand in Uganda may respond to a given subsidy. On the one hand, defining treatment too narrowly can place affected vehicles in the comparison group, violating the stable unit treatment value assumption (SUTVA). On the other hand, defining treatment too broadly assigns subsidy exposure to vehicles whose supply is unlikely to respond, attenuating the estimated effect. The treatment definition therefore needs to capture economically relevant responses without pooling together very different and thus likely irrelevant vehicles.

In choosing the treatment definition, I build on existing evidence for substantial within-make substitution in automobile purchases. Studies across countries, including Japan, document such a pattern and point to lower uncertainty about the quality of familiar makes and established relationships with affiliated dealerships as possible explanations (e.g., Mannering and Winston (1991), Kato (2021), Barwick et al. (2026), Huse and Lucinda (2026)). In Uganda, dealerships are generally not affiliated with particular makes, but anecdotal evidence similarly points to the importance of make-specific reputations for both reliability and ease of maintenance in consumers' choices.[21] In the main specification, I thus measure exposure to subsidies with the average Japanese subsidy among variants of the same make in each fiscal year. The estimating equation is:

$$\mathbb{E}[N_{gt} \mid X] = \exp\left[\beta^N Subsidy_{m(g),f(t)} + \alpha_g + \lambda_{b(g),y(t)} + \delta_{s(g),y(t)} + \gamma_{q(t)}\right].$$

[21] See https://www.monitor.co.ug/uganda/business/auto/which-brand-will-topple-toyota--1725240 for an example, last accessed October 2026.

Here, g denotes a group, defined as a make × model × age-bin combination, and t denotes a quarter. I group ages into seven bins: 0–5, 6–9, 10–13, 14–15, 16–17, 18–19, and 20+ years, following the thresholds used in Uganda's age-based import restrictions.[22] N_{gt} is the number of first-time registrations of group g in quarter t. For each make and model, I take the span from the earliest to the latest year of manufacture among its first-time registrations and include, in each quarter, every age bin consistent with a year of manufacture in that span, including group-quarter combinations with zero first-time registrations. $Subsidy_{m(g),f(t)}$ is the average subsidy in thousands of 2013 USD among subsidized new vehicles produced by make $m(g)$ in Japanese fiscal year $f(t)$. The specification includes group fixed effects α_g, age-bin-by-calendar-year fixed effects $\lambda_{b(g),y(t)}$, segment-by-calendar-year fixed effects $\delta_{s(g),y(t)}$, and quarter-of-year fixed effects $\gamma_{q(t)}$. It thus flexibly controls for permanent differences across groups and seasons, as well as differential changes over time across ages and segments, including those arising from changes in Uganda's age-based import tariffs and age limits over time. The coefficient of primary interest, β^N, is estimated from changes in subsidy exposure across makes and Japanese fiscal years. Standard errors are clustered at the make × Japanese fiscal year level, at which subsidy exposure varies.

The identifying assumption is that, absent changes in Japanese subsidies, first-time registrations of vehicles whose makes experience different changes in subsidy exposure would have followed parallel trends, conditional on the fixed effects. In particular, changes in Japanese subsidies must not be correlated with other make-specific shocks that differentially affect the demand for those vehicles in Uganda. This assumption is plausible, especially given that Japanese subsidies are unlikely to respond to demand conditions specific to Uganda.

Column (1) in Table 3 reports the baseline estimate. $\hat{\beta}^N$ is 0.056 and is statistically significant at the 1 percent level. This implies that a 1,000 USD increase in exposure to subsidies significantly increases expected first-time registrations by 5.8 (= $\exp(0.056) - 1$) percent.

The baseline estimate in Column (1) remains stable across alternative specifications that vary the timing and scope of subsidy exposure. Columns (2) and (3) add the average subsidy in the previous and following fiscal year, respectively. In both cases, the contemporaneous coefficient remains similar to the baseline estimate, while the lag and lead coefficients are smaller and statistically insignificant. In particular, the insignificant lead coefficient provides support for the conditional parallel-trend assumption. Column (4) adds the average subsidy among subsidized variants of other makes in the same segment and fiscal year. Its coefficient is small and statistically insignificant, while the own-make subsidy coefficient is nearly unchanged, lending support to the choice of make-level treatment. In Column (5), I instead define an observation as a make × model × age bin × exporter and assign subsidy exposure only to observations with vehicles exported from Japan. Correspondingly, I replace group fixed effects with group fixed effects interacted with an indicator for imports from Japan. The estimated coefficient is similar to the baseline estimate (p-value for the difference = 0.54),[23] consistent with the fact that vehicles were imported

[22] I combine ages 6–7 and 8–9 into a single bin because relatively few vehicles fall in these age ranges.

[23] I stack the samples of Columns (1) and (5) and estimate both specifications jointly using PPML, interacting all regressors and fixed effects with a sample indicator. Standard errors are clustered at the make × Japanese fiscal year level across the stacked samples, accounting for correlation between the two estimates. The p-value is from a Wald test of the difference between the two coefficients.

	Number of first-time registrations					
	(1)	(2)	(3)	(4)	(5)	(6)
$Subsidy_{m(g),f(t)}$	0.056***	0.046**	0.052**	0.057***		
	(0.020)	(0.019)	(0.021)	(0.020)		
$Subsidy_{m(g),f(t)-1}$		0.031				
		(0.021)				
$Subsidy_{m(g),f(t)+1}$			0.018			
			(0.021)			
$Subsidy^{rival}_{m(g),f(t)}$				-0.010		
				(0.013)		
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{\text{From Japan}\}_g$					0.054***	
					(0.019)	
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 0\text{–}5\}$						0.015
						(0.036)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 6\text{–}9\}$						0.161***
						(0.039)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 10\text{–}13\}$						0.110***
						(0.030)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 14\text{–}15\}$						-0.003
						(0.028)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 16\text{–}17\}$						-0.066
						(0.053)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 18\text{–}19\}$						-0.045
						(0.040)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 20+\}$						-0.021
						(0.074)
Age bin × Year FE	✓	✓	✓	✓	✓	✓
Group FE	✓	✓	✓	✓		✓
Group × Exporter FE					✓	
Segment × Year FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.831	0.832	0.832	0.832	0.852	0.832
Observations	24,640	24,640	24,068	24,640	45,480	24,640

Notes: Each observation is a group (make × model × age bin) in a quarter from January 2013 through June 2024 in Columns (1)–(4) and (6), and a group × exporter (Japan or other) combination in a quarter in Column (5). Subsidies are in thousands of USD. $Subsidy^{rival}_{m(g),f(t)}$ is the average subsidy among subsidized variants of other makes in the same segment. PPML drops observations whose fixed effects perfectly predict zero first-time registrations, such as groups with no first-time registrations during the sample period. Column (3) excludes April–June 2024, for which the following fiscal year's subsidy is unavailable. Standard errors clustered by make × fiscal year are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 3: Estimated effects on the number and composition of first-time registrations in Uganda

predominantly from Japan and hence explicitly distinguishing vehicles by exporter leaves the estimated effect largely unchanged. Because the online listings used to construct domestic prices rarely report exporters, the price measures constructed in Section 3 do not distinguish vehicles by exporter. I likewise do not define products by exporter in the structural model. The similarity of the estimates with and without distinguishing exporters suggests that this limitation is unlikely to

drive the results.

I next examine the effects of subsidies on the composition of first-time registered vehicles in Uganda. I extend the regression above to allow for bin-specific effects:

$$\mathbb{E}[N_{gt} \mid X] = \exp\left[\sum_k \beta_k^N Subsidy_{m(g),f(t)} \mathbf{1}\{b(g) = k\} + \alpha_g + \lambda_{b(g),y(t)} + \delta_{s(g),y(t)} + \gamma_{q(t)}\right]. \quad (1)$$

Column (6) reports the estimates, which are markedly different across bins. The increase in first-time registrations is concentrated among vehicles aged 6–13, with coefficients of 0.161 and 0.110, respectively, both statistically significant at the 1 percent level. In contrast, the estimated effects are small and statistically insignificant for vehicles aged 0–5 and 14 or older.

To translate the bin-specific estimates into changes in the overall age distribution, I estimate the implied distribution of first-time registrations in the absence of subsidies. For each group-quarter observation, I remove the estimated bin-specific effect of subsidies:

$$\hat{N}_{gt}^{no\ subsidy} = N_{gt} \exp\left(-\hat{\beta}_{b(g)}^N Subsidy_{m(g),f(t)}\right). \quad (2)$$

I then separately sum over the observed and counterfactual registrations within each age bin over quarters from January 2013 through June 2024. Figure 2 compares the observed and counterfactual age distributions. Over the years, Japanese subsidies increased the total number of first-time registrations by 7.1%. In addition, Japanese subsidies primarily increase the number of relatively young used vehicles first-time registered in Uganda, rather than shifting new registrations uniformly across the age distribution. Figure A11 further plots the subsidy-induced change in the share of first-time registrations of each bin. Translating these shifts into the change in the average age using the sample average age within each bin, I find that subsidies reduce the average age by 0.350 years, or 2.48 percent, relative to the case without subsidies. The standard error from a parametric bootstrap is equal to 0.119 years, yielding a p-value of 0.004.[24]

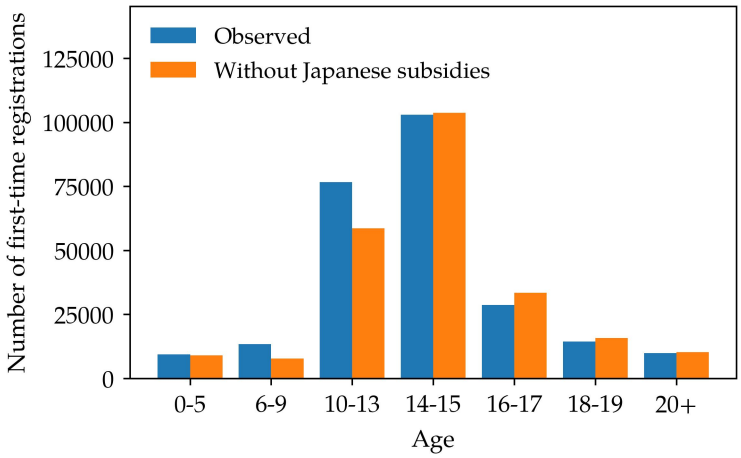
4.2 Effects on the Prices of First-Time Registered Vehicles

To estimate the effect of Japanese subsidies on domestic prices of first-time registered cars in Uganda, I use the same explanatory variables and fixed effects as in Section 4.1, but replace the number of first-time registrations with the average domestic price p_{gt} across make × model × age combinations within group g (make × model × age bin) in quarter t.[25] I estimate the regressions using ordinary least squares (OLS). For example, the estimating equation for the baseline specification is:

$$p_{gt} = \beta^p Subsidy_{m(g),f(t)} + \alpha_g + \lambda_{b(g),y(t)} + \delta_{s(g),y(t)} + \gamma_{q(t)} + u_{gt}.$$

[24] For each bootstrap draw, I jointly draw the bin-specific subsidy coefficients from their estimated asymptotic multivariate normal distribution, reconstruct the implied bin-specific total number of registrations without subsidies, and recompute the change in the average age.

[25] When computing average domestic prices for groups aged 0–15 in a quarter, I include only make–model–age combinations with at least one first-time registration in that quarter.



Notes: The figure compares observed first-time registrations in Uganda from January 2013 through June 2024 with counterfactual first-time registrations in the absence of Japanese subsidies. For each make × model × age-bin group and quarter, counterfactual registrations are calculated by removing the estimated age-bin-specific effects of Japanese subsidies. Registrations are then summed across groups and quarters within each age bin.

Figure 2: The number of first-time registrations

I focus on January 2019 through June 2024 because of the more complete and stable price coverage over this period, as discussed in Section 3. In addition, because Uganda banned imports of vehicles more than 15 years old throughout this period, Columns (1)–(5) of Table 4 estimate the effects on average domestic prices only for groups aged 0–15.[26]

Column (1) in Table 4 presents the baseline estimate. The estimate implies that a 1,000 USD increase in exposure to subsidies reduces the average price by 325 USD, with a standard error of 116 USD, or 2.6 percent of the median price of 12,465 USD among vehicles aged 0–15 in the sample. The estimate is statistically significant at the 1 percent level. Similar to the estimated effect on quantities, Columns (2)–(4) show that the estimated effect on prices is stable across alternative specifications that take the same forms as those in Section 4.1.

Moreover, the bin-specific effects on prices closely mirror the bin-specific effects on quantities. In Column (5), I estimate the price effect separately for each age bin as in Equation (1). The largest and most precisely estimated price declines occur among vehicles aged 6–13, the same ages that exhibit the largest increases in the number of first-time registrations. The estimates show that a 1,000 USD increase in the average subsidy reduces prices by 557 USD for vehicles aged 6–9 and by 327 USD for those aged 10–13, with both estimates statistically significant at the 5 percent level. The estimated effect for vehicles aged 14–15 is smaller, at 197 USD, and statistically significant at the 10 percent level, while the effect for vehicles aged 0–5 is insignificant.

Column (6) extends the sample to also include domestic prices corresponding to cars aged 16 and above. Since such vehicles are no longer legally eligible for import, the effect of Japanese subsidies on their domestic prices reflects spillovers through the domestic used-vehicle market rather than a direct effect on their foreign supply. The estimates show that a 1,000 USD increase in the average subsidy reduces domestic prices of vehicles aged 16–17 by 211 USD, an effect that is

[26] Between January 2013 and December 2018, 37% of first-time registrations in the sample are associated with cars above 15 years old, while it is only 2.1% between January 2019 and June 2024.

	Domestic price (thousand 2013 USD)					
	(1)	(2)	(3)	(4)	(5)	(6)
$Subsidy_{m(g),f(t)}$	-0.325***	-0.336***	-0.296***	-0.329***		
	(0.116)	(0.114)	(0.103)	(0.119)		
$Subsidy_{m(g),f(t)-1}$		0.036				
		(0.080)				
$Subsidy_{m(g),f(t)+1}$			-0.199			
			(0.128)			
$Subsidy^{rival}_{m(g),f(t)}$				0.079		
				(0.200)		
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 0\text{–}5\}$					-0.315	-0.253
					(0.976)	(0.987)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 6\text{–}9\}$					-0.557**	-0.553**
					(0.276)	(0.274)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 10\text{–}13\}$					-0.327**	-0.308**
					(0.147)	(0.151)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 14\text{–}15\}$					-0.197*	-0.165*
					(0.099)	(0.094)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 16\text{–}17\}$						-0.211*
						(0.117)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 18\text{–}19\}$						-0.012
						(0.105)
$Subsidy_{m(g),f(t)} \times \mathbf{1}\{b(g) = 20+\}$						0.034
						(0.137)
Age bin × Year FE	✓	✓	✓	✓	✓	✓
Group FE	✓	✓	✓	✓	✓	✓
Segment × Year FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
R^2	0.929	0.929	0.928	0.929	0.929	0.937
Observations	2,464	2,464	2,315	2,464	2,464	3,996

Notes: Each observation is a group (make × model × age bin) in a quarter from January 2019 through June 2024. Columns (1)–(5) use groups aged 0–15, with average prices computed across make–model–age combinations with at least one first-time registration in the quarter; Column (6) adds groups aged 16 and above. Prices and subsidies are in thousands of 2013 USD. $Subsidy^{rival}_{m(g),f(t)}$ is the average subsidy among subsidized variants of other makes in the same segment. Column (3) excludes April–June 2024, for which the following fiscal year's subsidy is unavailable. Standard errors clustered by make × fiscal year are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4: Estimated effects on domestic prices in Uganda

statistically significant at the 10 percent level. The estimated effects become substantially smaller for older vehicles and are not statistically significant for vehicles aged 18–19 or 20 and above. The concentration of the spillover among vehicles just above the age limit is consistent with younger imported vehicles exerting the strongest competitive pressure on vehicles above the age limit that are the closest substitutes.

4.3 Interpretation and Limitations

The DiD estimates in Tables 3 and 4 suggest that increases in make-level exposure to Japanese subsidies raised the number of first-time registered vehicles in Uganda and reduced their domestic

prices, with the largest effects concentrated among vehicles aged 6–13. The findings provide evidence for a price channel through which Japanese subsidies affect the number and composition of first-time registrations in Uganda. The counterfactual analysis, with first-time registrations in the absence of Japanese subsidies constructed according to Equation (2), further quantifies the aggregate effects of the subsidies on the number and age composition of first-time registrations. There are, however, two potential concerns with this approach.

First, DiD estimates in Tables 3 and 4 are identified from differences in outcomes across makes with different exposure to subsidies, conditional on fixed effects, and may differ from the effects of each make's subsidies on its own outcomes, holding other makes' subsidies fixed. One source of such differences is substitution across makes in Japan and Uganda. Subsidies on a given make may lead to changes in the prices of other makes in Uganda through substitution across makes in Japan, while substitution across makes in Uganda may affect first-time registrations of other makes even if their own prices remain unchanged. In addition, fleet dynamics can bias the DiD estimates even in the absence of cross-make substitution. For example, past Japanese subsidies for a given make may have increased first-time registrations of that make in Uganda, raising its domestic stock at older ages in subsequent years and potentially reducing demand for imports at those ages. If past and current subsidies are correlated, the estimated effects of current subsidies may partly, but not necessarily fully, reflect these dynamic responses. Therefore, DiD estimates can overstate or understate the effects of each make's subsidies on its own prices and first-time registrations.[27]

Second, the counterfactual removes only the estimated effects of each make's own subsidies and thus does not account for the effects of other makes' subsidies on its first-time registrations. However, cross-make substitution in Japan and Uganda can cause a given make's first-time registrations to respond to subsidies on other makes, with the resulting changes in its domestic stock also affecting first-time registrations in subsequent years. Consequently, the counterfactual may overstate or understate the aggregate effects of Japanese subsidies on first-time registrations, even if the DiD estimates correctly reflect the effects of a given increase in each make's subsidies on its own first-time registrations, holding other makes' subsidies fixed.

Though the robustness checks in Tables 3 and 4 suggest that the concerns may be limited, I develop a structural model that allows for both substitution across makes and fleet dynamics in Uganda in estimating the effects of Japanese subsidies on first-time registrations. I take the estimated effects of Japanese subsidies on prices of first-time registered vehicles in Column (6) of Table 4 as given in counterfactual simulations, and decompose the difference in the estimated aggregate effects of Japanese subsidies between the DiD and structural approaches into components corresponding to the two concerns. The comparison is therefore conditional on the estimated price effects from the DiD regression.

Besides first-time registrations, the model allows me to estimate the effects of Japanese subsidies on scrappage, emissions, and overall welfare in Uganda. It also allows me to evaluate counterfactual

[27] For example, subsidies for new Toyotas may induce Japanese Nissan owners to replace their vehicles with Toyotas, increasing the supply of used Nissans and lowering their prices in Uganda. To the extent that this increases Nissan registrations in Uganda, the resulting increase in Nissan registrations would lead the DiD estimates to understate the effects on Toyotas. Conversely, if lower Toyota prices draw demand away from Nissans in Uganda, the estimates may overstate the effects on Toyotas. When both mechanisms are present, their effects on Nissan registrations may offset each other, leaving the DiD estimates on the number of registrations unaffected.

changes in Uganda's import restrictions.

5 Model

I adapt the dynamic equilibrium model of vehicle supply and demand in Jacobsen et al. (2023) to an open-economy setting in which inflows into the domestic fleet occur through imports. The model combines static demand for differentiated vehicles with endogenous inflows and scrappage, which jointly determine the evolution of the domestic fleet over time.

Environment Time is discrete, with each period corresponding to a calendar year t. Each product j is defined by a make, model, and exact age $a(j)$. In each year, the set of products available in the domestic market, $\mathcal{J}_t$, includes products with a positive inherited stock and products that can be imported under the prevailing import-age limit. The importable subset, $\mathcal{I}_t \subseteq \mathcal{J}_t$, includes products aged at or below the limit with positive first-time registrations in the baseline data. Counterfactuals can change the importable set, prices, first-time registrations, and which importable products have positive first-time registrations, but cannot introduce importable products that are absent from the baseline data.

Static demand and supply Consumer i has exogenous income y_i and chooses among the products in the available choice set $\mathcal{J}_t$ and the outside option $j = 0 \notin \mathcal{J}_t$. If the consumer chooses product j at domestic price p_{jt}, he or she receives one year of vehicle services and can retain or resell the vehicle as the same make and model one year older at the beginning of the following year at no transaction cost, subject to repair costs and scrappage.

Preferences do not depend on past choices. The non-price utility consumer i derives from one year of services from product j is $X'_{jt}\beta + \xi_{jt} + \epsilon_{ijt}$, where X_{jt} are observed product characteristics and year fixed effects, ξ_{jt} is an unobserved product-level demand shock, and ϵ_{ijt} is an idiosyncratic preference shock. In particular, the observed product characteristics include engine size,[28] weight, a quadratic in age, and make fixed effects. The utility from the outside option is $u_{i0t} = \epsilon_{i0t}$. I assume that the idiosyncratic preference shocks follow a nested logit structure and that vehicles of the same make belong to the same nest, with the nesting parameter σ determining the degree of within-make substitution. The outside option forms its own nest. Consumers take prices as given. Monetary payments and receipts enter utility linearly with coefficient $\alpha > 0$.

At the beginning of each year t, consumers collectively hold a stock K_{jt} of product j carried over from the previous year. Each vehicle in this stock draws a repair cost c from an age-specific distribution $F_a(c)$, after which its owner decides whether to repair or scrap the vehicle. Under the normalization that the scrap value of all vehicles is zero,[29] the owner receives zero if he or she scraps

[28] Consumers and dealers in Uganda often assess fuel efficiency based on engine size rather than fuel economy. See https://www.monitor.co.ug/uganda/business/auto/considerations-before-buying-a-car-1608300 for an example, last accessed October 2026. I therefore include engine size but not fuel economy as an observed product characteristic. The estimated coefficient on engine size therefore reflects both preferences for engine size itself and its perceived association with fuel efficiency.

[29] For the scrappage decision, a positive scrap value that is common across vehicles of the same age can equivalently

the vehicle, whereas repairing and reselling it yields $p_{jt} - c$. Because retaining a repaired vehicle is equivalent to selling and repurchasing it when transactions are costless, the same comparison applies regardless of whether the owner decides to retain it.

Consumers maximize the expected discounted sum of per-period utilities over an infinite horizon, with an income-dependent discount factor $d(y_i) \in (0, 1)$ that is increasing in income. This may reflect, for example, higher borrowing costs or tighter credit constraints that lead lower-income consumers to discount future cash flows more. In Appendix C.1, I provide a microfoundation for this income-dependent discount factor. Under the assumptions, Appendix C.2 shows that the dynamic problem is equivalent to a static choice of one year of vehicle services and that the repair decision can be optimized separately from the vehicle choice.

In particular, the optimal repair decision is to repair the vehicle if $c < p_{jt}$ and scrap it otherwise. The resulting scrappage probability is

$$h_{jt} = 1 - F_{a(j)}(p_{jt}).$$

The stock of product j that survives scrappage is

$$S_{jt} = (1 - h_{jt})K_{jt}. \tag{3}$$

I assume stationary expectations over prices, so that consumers expect the price schedule in the following year to be the same as the current price schedule. The expected net resale value of vehicle j is therefore

$$R_{jt} = \mathbb{E}\left[(p_{j^+t} - c)_+\right],$$

where j^+ denotes the same make and model one year older,[30] $c \sim F_{a(j^+)}$, and $(x)_+ = \max\{x, 0\}$.

The utility from choosing product j is

$$u_{ijt} = X'_{jt}\beta - \alpha\left[p_{jt} - d(y_i)R_{jt}\right] + \xi_{jt} + \epsilon_{ijt}. \tag{4}$$

That is, consumers choose among vehicles based on the non-price utility from one year of services and the user cost, $r_{jt}(y_i) = p_{jt} - d(y_i)R_{jt}$.

Define $\delta_{jt} = X'_{jt}\beta - \alpha p_{jt} + \xi_{jt}$. Conditional on income y, the probability of choosing product j is

$$s_{jt}(y) = \frac{\exp\left(\frac{\delta_{jt} + \alpha d(y)R_{jt}}{1-\sigma}\right)}{D_{m(j)t}(y)} \cdot \frac{D_{m(j)t}(y)^{1-\sigma}}{1 + \sum_m D_{mt}(y)^{1-\sigma}},$$

be incorporated into the repair-cost draw. If scrapping an age-a vehicle yields s_a, the vehicle is repaired whenever $p_{jt} - c \geq s_a$, or equivalently whenever $p_{jt} \geq c + s_a$. The repair-cost distribution estimated below can therefore be interpreted as the distribution of the effective repair cost $c + s_a$, which incorporates any age-specific scrap value common across vehicles.

[30] In the structural estimation sample, around 3% of cars in each market have a successor j^+ that is not in the choice set $\mathcal{J}_t$. In these cases, I assume that consumers form expectations about its future resale price based on the current price schedule extended to unavailable products. Sections 6 and 7 describe the implementation under different policy scenarios.

where

$$D_{mt}(y) = \sum_{k \in \mathcal{J}_t : m(k)=m} \exp\left(\frac{\delta_{kt} + \alpha d(y) R_{kt}}{1-\sigma}\right)$$

is the within-make sum of exponentiated utilities for make m. Because consumers differ in income, demand for each product aggregates choice probabilities over the income distribution in year t, $F_t(y)$. Denote the market size in year t as $\mathcal{M}_t$. The aggregate market share and demand for product j are

$$s_{jt} = \int s_{jt}(y) dF_t(y), \qquad Q^d_{jt} = \mathcal{M}_t s_{jt}.$$

The outside-option share is $s_{0t} = 1 - \sum_{j \in \mathcal{J}_t} s_{jt}$.

In addition to the surviving domestic stock, vehicles can enter the market through first-time registrations. Given that Uganda accounted for only a small share of the Japanese used-vehicle export market (Section 3.2), I assume that foreign supply is perfectly elastic at exogenous landed prices $\bar{p}_{jt}$ for importable products $j \in \mathcal{I}_t$.[31] For importable products, the no-arbitrage condition between imports and domestic stocks implies that domestic prices cannot exceed landed prices and equal them whenever these products are imported. For importable products that are not imported or non-importable products, domestic prices adjust to equate demand with surviving domestic stocks.

Equilibrium Given the inherited stocks K_{jt} and landed prices $\bar{p}_{jt}$, an equilibrium in year t consists of domestic prices $p_t = (p_{jt})_{j \in \mathcal{J}_t}$ and first-time registrations $(N_{jt})_{j \in \mathcal{J}_t}$ that clear every market.

For importable products $j \in \mathcal{I}_t$, first-time registrations cover the difference between demand and the surviving domestic stock when the domestic price equals the landed price. Otherwise, the number of first-time registrations is zero and the domestic price can fall below the landed price. That is,

$$Q^d_{jt}(p_t) = S_{jt}(p_{jt}) + N_{jt}, \qquad N_{jt} \geq 0, \qquad p_{jt} \leq \bar{p}_{jt}, \qquad N_{jt}(\bar{p}_{jt} - p_{jt}) = 0, \qquad j \in \mathcal{I}_t. \tag{5}$$

For products outside $\mathcal{I}_t$, there are no first-time registrations:

$$N_{jt} = 0, \qquad Q^d_{jt}(p_t) = S_{jt}(p_{jt}), \qquad j \in \mathcal{J}_t \setminus \mathcal{I}_t. \tag{6}$$

In Appendix C.3, I establish the existence of equilibrium under mild regularity conditions that hold under the estimated model. While I do not formally establish uniqueness, I solve for equilibrium from multiple starting points and converge to the same solution in the simulations in Section 7.

[31] This assumption also requires that markups of domestic intermediaries, such as importers and dealers, do not respond to changes in domestic demand. However, the estimated effects of Japanese subsidies on domestic prices may already reflect such responses, which are accounted for in the analysis. I nevertheless abstract from other markup adjustments, such as those that could arise under tighter import-age restrictions.

Dynamic fleet evolution In each year t, the domestic fleet consists of both new inflows and vehicles carried over from the previous period that survive scrappage. The number of vehicles of product j is

$$M_{jt} = S_{jt} + N_{jt}. \tag{7}$$

The domestic fleet in year t becomes the stock carried over to the following year, with each vehicle aging deterministically by one year:

$$K_{j^+,t+1} = M_{jt}. \tag{8}$$

Through this process, first-time registrations and scrappage jointly determine the evolution of the size and composition of the domestic fleet.

6 Estimation

I estimate the parameters of the structural model using generalized method of moments (GMM). The estimation combines data on first-time vehicle registrations, domestic prices, consumers' incomes, and the age distribution of vehicles on the road in Uganda.

6.1 Parameterization

Because few first-time registrations and online listings involve vehicles older than 35 years, I impose a maximum age of 35. Vehicles that remain in service at age 35 provide services during that year and are scrapped with certainty upon reaching age 36. For vehicles aged 35 or younger, I assume that repair costs follow an age-specific Pareto distribution with support $[\ell_{a(j)}, \infty)$. The scrappage hazard then takes the form

$$h_{jt} = b(a(j))p_{jt}^{\gamma}, \qquad p_{jt} \geq \ell_{a(j)} = b(a(j))^{-1/\gamma},$$

and equals one for prices below $\ell_{a(j)}$. The parameter γ is the constant elasticity of the scrappage hazard with respect to prices,[32] while $b(a(j))$ is an age-specific scale parameter. For prices above $\ell_{a(j)}$, the expected repair cost conditional on survival, $\bar{c}_{jt}$, has a closed-form expression, as presented in Appendix D.2.

Instead of estimating $b(a(j))$ freely for each age, I parameterize it as

$$b(a(j)) = \bar{h}(a(j)) \left(\frac{1}{\tilde{p}_{a(j)}}\right)^{\gamma},$$

where $\tilde{p}_a$ is the median observed price of age a and

$$\bar{h}(a) = \Lambda\left(\vartheta_0 + \vartheta_1 \frac{a}{10}\right), \qquad \Lambda(z) = (1 + \exp(-z))^{-1}.$$

[32] Jacobsen et al. (2023) additionally allow the price elasticity of scrappage to vary with age, and calibrate $b(a(j))$ and $\gamma_{a(j)}$ at all ages. I instead parameterize $b(a(j))$ and restrict γ to be common across ages to reduce the number of jointly estimated parameters.

That is, $\bar{h}(a)$ is the hazard at the median price. ϑ_0 and ϑ_1 determine the level and age gradient of scrappage.

I parameterize the income-dependent discount factor as a logistic function of income:

$$d(y) = \varrho \Lambda \left(\theta \left[\ln y - \kappa \right] \right), \tag{9}$$

and set $\varrho = 0.95$. The parameter κ is a location parameter that shifts this relationship along the income distribution, while θ determines its steepness.

6.2 Estimator

There are five markets, each corresponding to a year between 2019 and 2023. The size of each market is the number of individuals aged 20 or older with an annual income of at least 15 million 2013 UGX (approximately 5,800 2013 USD) in that year.[33] Given the evidence in Section 3.1 that the income distributions in the PAYE data and broader population are comparable above the income threshold, I use the conditional distribution from the PAYE data for $F_t(y)$ in each year. The nonlinear parameters to be searched over are $\phi = (\gamma, \vartheta_0, \vartheta_1, \theta, \kappa, \sigma, \alpha)$, while the coefficients β on observed characteristics and year fixed effects are estimated conditional on nonlinear parameters in each iteration.

The estimation algorithm proceeds as follows. For a given set of nonlinear parameters, I first construct the stock of each product in each year. Because I do not observe the stock at the beginning of 2019, I reconstruct it from historical first-time registrations between 2000 and 2018 and the implied survival probabilities:

$$K_{j,2019} = \sum_{\tau=\max\{2000,\, 2019-a(j)\}}^{2018} N_{j^{-(2019-\tau)},\tau} \prod_{s=\tau+1}^{2018} \left(1 - h_{j^{-(2019-s)},s}\right),$$

where $j^{-\ell}$ is the same make and model as j, but ℓ years younger. Given $K_{j,2019}$ and first-time registrations between 2019 and 2023, the stock of product j in service in year t, M_{jt}, then follows from equations (3), (7), and (8).[34] Appendix D.6 shows that the structural parameter estimates are

[33] Motorization rates in Uganda are very low. For example, Uganda had fewer than 4 passenger cars per 1,000 people in 2019, compared with 360 in the United States. This suggests that most Ugandans are unlikely to participate in the market. I therefore restrict the potential market to individuals with annual income above 15 million 2013 UGX, approximately half the median price among all cars registered for the first time between 2019 and 2023, taking into account the commonly offered two- to three-year dealer financing terms in Uganda. For each year, I compute the market size as the share of individuals with an annual income larger than 15 million 2013 UGX in the 2019/20 UNPS times the number of people aged 20 years or older in that year in Uganda from PopulationPyramid.net. When computing the share, I weight individuals using household sampling weights to account for differences in the probability of individuals being selected into the survey. In the end, the inside share is between 0.36 and 0.39 in the 5 markets. See https://www.helgilibrary.com/indicators/passenger-cars-per-1000-people/uganda, https://www.helgilibrary.com/indicators/passenger-cars-per-1000-people/usa, and https://www.populationpyramid.net/uganda/ for detailed statistics, last accessed October 2026.

[34] I treat the 2.1% of first-time registrations between 2019 and 2023 that are above the 15-year age limit as exogenous inflows that add to the stock in service of the corresponding product, and their prices clear the domestic market together with the rest of that product's stock in service. Under the tighter 13-year limit in Section 7, these inflows are removed as well.

robust to the choice of the starting year for reconstructing the initial stock in 2019, with 2005 as an alternative to 2000.

Given M_{jt}, I construct the observed market shares as

$$s_{jt}^{obs} = \frac{M_{jt}}{\mathcal{M}_t}.$$

With the given set of the nonlinear parameters, I compute R_{jt} and the income-specific utility component $\alpha d(y)R_{jt}$.[35] Because $\alpha d(y_i)R_{jt}$ is fixed with respect to δ_{jt} for given nonlinear parameters, the demand system is a special case of the heterogeneous-coefficient nested-logit model in Grigolon and Verboven (2014). I thus follow their contraction mapping to recover δ_{jt} from observed market shares. Specifically, I iterate

$$\delta_{jt}^{r+1} = \delta_{jt}^{r} + (1-\sigma)\left[\log s_{jt}^{obs} - \log s_{jt}\left(\delta_t^r\right)\right]$$

until the predicted market shares converge to their observed counterparts.

Given the recovered $\hat{\delta}$, the first set of GMM moments is constructed from the orthogonality conditions $\mathbb{E}[Z_{jt}\xi_{jt}] = 0$, where Z_{jt} contains X_{jt} and the excluded instruments. The excluded instruments are the annual make-level average subsidy,[36] its interactions with indicators for the 6–9, 10–13, and 14–15 age bins, lagged annual make-level average subsidy, the number of available products of the same make and its square, and the number of available products from other makes in the same segment within one year of the product's own age. For each candidate set of nonlinear parameters, I concentrate out the linear parameters β using

$$\hat{\beta} = \left(X'ZW_DZ'X\right)^{-1} X'ZW_DZ'(\hat{\delta} + \alpha p), \tag{10}$$

where W_D is the weighting matrix for this set of moments. The estimates of the unobserved product-level demand shocks are then $\hat{\xi}_{jt} = \hat{\delta}_{jt} + \alpha p_{jt} - X'_{jt}\hat{\beta}$, and the moments are

$$g_D = \frac{1}{N}\sum_{jt} Z_{jt}\hat{\xi}_{jt}.$$

The second block of moments matches the model-implied age distribution of the fleet in July 2024 to the observed distribution across seven age groups in the random sample from Crowe et al. (2025). I construct the stock carried into July 2024 using the stock inherited at the beginning of the year, first-time registrations in the first two quarters, and quarterly scrappage probabilities derived from the model's annual probabilities. The vector of moments, g_A, contains the differences between the model-implied and observed age shares for six of the seven groups, omitting one because the shares sum to one. The exact formulas are in Appendix D.2.

[35] When j^+ is not in the choice set $\mathcal{J}_t$, I compute R_{jt} at the predicted price of j^+ from the same hedonic price regressions that impute missing prices for available products, described in Appendix A.3.

[36] Since subsidies change across fiscal years while each market is a calendar year, I construct annual subsidy exposure as one-fourth of the previous fiscal year's make-level average subsidy plus three-fourths of the current fiscal year's average subsidy.

The final block of moments, g_I, targets income sorting across products among first-time registrants with matched annual income. I match the observed and model-implied mean log annual income of registrants at each product age with at least 100 matched registrants between 2019 and 2023, covering thirteen ages at or below 15.[37] I also match the observed and model-implied mean log annual income of registrants corresponding to each price tercile within the same age bins, 0–5, 6–9, 10–13, and 14–15, as in Section 4, demeaned across price terciles within each age bin. Appendix D.2 provides the exact formulas.

I stack the three sets of moments and estimate the structural parameters using efficient two-step GMM. The weighting matrix and standard errors account for correlation within make-by-year clusters and sampling uncertainty in the observed age distribution.

6.3 Identification

The orthogonality conditions, g_D, identify the price coefficient α and nesting parameter σ. Evidence from Section 4.2 shows that Japanese subsidies lower domestic prices of the subsidized make, with heterogeneous effects across vehicle ages. Current subsidies and their interactions with age-bin indicators therefore provide plausibly exogenous price variation that identifies α. The numbers of available products within the same make and from other makes in the same segment at adjacent ages are differentiation IVs as in Gandhi and Houde (2019). Variation in the numbers shifts substitution within and across nests, allowing σ to be identified separately from α. Their exclusion restrictions require the number and ages of competing products to be uncorrelated with unobserved demand shocks for a given product, conditional on that product's observed characteristics and year fixed effects. Conditional on the nonlinear parameters, the linear demand parameters are identified from variation in the corresponding regressors.

The age-distribution moments, g_A, identify the scrappage parameters $(\gamma, \vartheta_0, \vartheta_1)$. Given historical first-time registrations and subsequent age and price paths, the model determines cumulative survival probabilities. Variation in the time since first registration provides identifying variation for the overall level of the scrappage hazard, ϑ_0, while variation in the ages over which vehicles have been exposed to scrappage provides identifying variation for its age gradient, ϑ_1. Conditional on ϑ_0 and ϑ_1, variation in prices relative to the age-specific median pins down γ through differences in survival across vehicles with different price histories.[38] In Appendix D.1, I further illustrate identification of the scrappage parameters with a simple example.

Moreover, lagged subsidies provide additional information about γ through their effects on historical prices and hence reconstructed surviving stocks. If $|\gamma|$ is too large, the model exaggerates differences in scrappage associated with subsidy-related price differences. The demand inversion can then translate these systematic errors in reconstructed shares into a correlation between estimated unobserved product-level shocks and subsidies, violating the corresponding orthogonality

[37] The thirteen ages are 1, 3, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 and 15.

[38] The model accounts for the feedback between prices and scrappage through equilibrium market clearing. Nevertheless, estimates of γ may be biased if unobserved determinants of scrappage are correlated with prices. Evidence from the existing literature suggests that such concerns may be quantitatively limited. For example, in the U.S., Jacobsen and Van Benthem (2015) find relatively small differences between OLS and IV estimates of the price elasticity of scrappage, while Busse et al. (2012) find no significant increase in used-vehicle prices following a Cash for Clunkers program.

condition in g_D.

Identification of θ and κ comes from income sorting across products with different resale values, as reflected in the income moments, g_I. For two products j and k, the contribution of the difference in the resale values to the relative utility is $\alpha d(y)(R_j - R_k)$. Because $d(y)$ increases with income, products with higher resale values are relatively more attractive to consumers with higher incomes, which in turn gives rise to differences in the income composition of consumers across products. Differences in the mean income both across ages and across price terciles within age bins summarize this sorting and therefore restrict the shape of $d(y)$.[39] Under the logistic specification, the income level at which the implied $d(y)$ reaches $\varrho/2$ identifies κ, while the rate at which $d(y)$ changes with log income identifies θ.

6.4 Estimates

Panel A of Table 5 reports the estimated nonlinear utility parameters, and Table A4 reports the estimated linear utility parameters. The nonlinear utility parameters are all statistically significant at the 1% level. In line with expectations, $\hat{\alpha} > 0$ and $0 < \hat{\sigma} < 1$. The relatively large estimate of σ indicates strong substitution within makes, consistent with the lack of evidence for cross-make spillovers in Section 4. The positive estimate of θ implies that the discount factor increases with income, while the estimate of κ implies that $d(y) = \varrho/2$ at an annual income of $\exp(\hat{\kappa}) =$ 7.6 thousand 2013 USD, approximately the 25th percentile of the income distribution among individuals included in each market. Figure A16 further plots the distribution of implied discount factors across individuals in each year. The median own-user-cost elasticity across products in the 2023 market is -3.67, and the median share of diverted demand going to other products of the same make is 0.73.[40] The estimated linear utility parameters indicate that consumers generally prefer newer and heavier vehicles with larger engines.

Panel B of Table 5 reports the estimated scrappage parameters, all of which are statistically significant at the 1% level. The estimates suggest that scrappage probabilities increase with the age and decrease with the prices. Evaluated at the age-specific median price, the estimated annual scrappage probability rises from 0.9% at age 0 to 2.6% at age 10 and 7.2% at age 20. The estimated elasticity of the scrappage probability with respect to price is $\hat{\gamma} = -0.837$, meaning that a 1% increase in price reduces the scrappage probability by approximately 0.84%. Figure A15 plots the estimated scrappage probabilities for ages up to 35 years and prices observed in the data.

The estimated model also closely reproduces the patterns targeted in estimation. Figure A12 shows that the model-implied and observed age distributions of the fleet in July 2024 are comparable. Figures A13 and A14 show that the model also closely reproduces observed income sorting across age bins and price terciles.

[39] Differences in the mean income across age groups reflect income sorting across products of different ages, while differences in the mean income across price terciles within age groups reflect additional sorting across products of different prices conditional on having similar ages.

[40] See Appendix D.2 for the exact formulas.

Parameter	Estimate	S.E.
Panel A. Utility		
Price coefficient (α)	0.318^{***}	(0.075)
Discount factor: constant (κ)	2.030^{***}	(0.179)
Discount factor: log income coefficient (θ)	2.962^{***}	(0.558)
Nesting parameter (σ)	0.732^{***}	(0.087)
Panel B. Scrappage hazard		
Constant (ϑ_0)	-4.691^{***}	(0.521)
Age coefficient (ϑ_1)	1.064^{***}	(0.206)
Price elasticity (γ)	-0.837^{***}	(0.249)

Notes: The table reports estimates of nonlinear structural parameters from joint GMM estimation. Standard errors are GMM sandwich standard errors clustered at the make × year level. Prices and incomes are in thousands of 2013 USD. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 5: Nonlinear structural parameter estimates

7 Counterfactuals

With the estimated model, I first estimate the effects of the Japanese subsidies on fleet dynamics, emissions, and overall welfare in Uganda. Second, I show that Japanese subsidies can change the tradeoffs associated with Uganda's import restrictions and thus their preferred design. Specifically, I compare the effects of tightening the maximum import age from 15 to 13 years with and without the subsidies. For each scenario, I solve for the equilibrium paths of prices, inflows, and scrappage, and then compute the resulting changes in emissions and overall welfare.

7.1 Simulation Algorithm

I consider four scenarios, indexed with $\omega = (s, A) \in \{0, 1\} \times \{13, 15\}$, where s indicates subsidies removed ($s = 0$) or in place ($s = 1$), and A indicates a maximum import age of 13 or 15 years. The scenario $\omega = (1, 15)$ corresponds to the baseline. The presence of subsidies directly changes the landed prices of importable products. During the in-sample period, 2019–2023, their landed prices in scenario ω are

$$\bar{p}_{jt}^{\omega} = \begin{cases} \bar{p}_{jt} & s = 1 \\ \bar{p}_{jt} - \hat{\beta}^{p}_{b(j)} \, \tilde{S}_{m(j),t} & s = 0, \end{cases} \tag{11}$$

where $\bar{p}_{jt}$ is the baseline landed price of product j in year t, $\tilde{S}_{m(j),t}$ is the annual average subsidy among cars of the same make as j in calendar year t, $b(j)$ is the age bin of product j, and $\hat{\beta}^{p}_{b(j)}$ is the estimated bin-specific effect of subsidies on prices reported in Column (6) of Table 4. For non-importable products, $\bar{p}_{jt}^{\omega} = \infty$. The age limit decides the set of importable products. For an age limit $A \in \{13, 15\}$, the importable set is

$$\mathcal{I}_t(A) = \left\{ j : \; a(j) \leq A, \; N_{jt} > 0 \right\},$$

where N_{jt} is the observed number of first-time registrations of product j in year t in the baseline. Thus, lowering the age limit from 15 to 13 removes products aged 14–15 from the importable set.

The simulation proceeds recursively, starting from the same initial stock in 2019 across scenarios, $K^{\omega}_{j,2019} = K_{j,2019}$, as reconstructed in Section 6, and solving for equilibrium one year at a time. In each year t, I take the inherited stocks K^{ω}_{jt}, the set of importable products $\mathcal{I}_t(A)$, and their landed prices $\bar{p}^{\omega}_{jt}$ as given. I hold the unobserved demand shocks ξ_{jt} and the linear structural parameters at their estimates. Given these inputs, I use a damped Newton method to solve for equilibrium prices $(p^{\omega}_{jt})_{j\in\mathcal{J}_t}$, imposing the constraint that prices of importable products cannot exceed their landed prices.[41] In each iteration, I compute demand and surviving stocks at the candidate prices, following the equations in Section 5. Once the equilibrium in year t is found, I compute the stocks carried over from year t to year $t+1$ and repeat the procedure.

To account for the effects of Japanese subsidies and Uganda's import restrictions on emissions and overall welfare that unfold over time, I also extend the simulation past 2023, which requires assumptions about the post-sample environment. From 2024 onward, I hold common exogenous demand conditions at their 2023 levels across scenarios,[42] while keeping the set of importable products and their landed prices fixed at their respective 2023 levels in each scenario. For emissions, I extrapolate the estimated declining trend across production cohorts, while allowing local pollutant emissions to increase with age. Appendix A describes the construction of the post-sample emissions in detail.

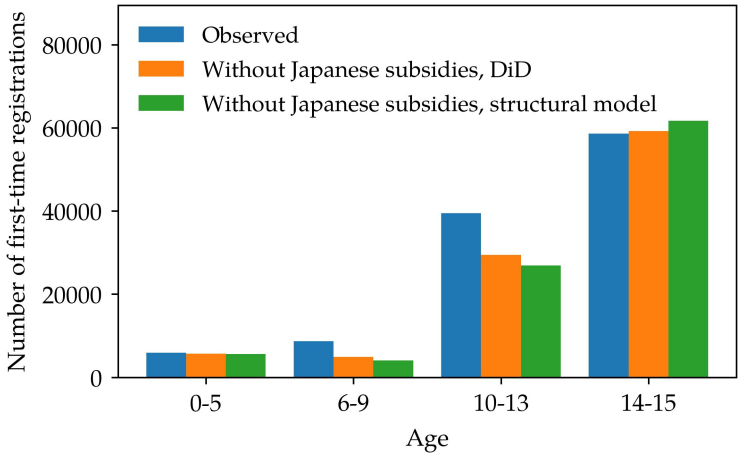
7.2 Effects of Japanese Subsidies in Uganda

I first compare the model-implied effects of Japanese subsidies on first-time registrations with the DiD estimates in Section 4. Figure 3 compares the observed number of first-time registrations between 2019 and 2023 with the counterfactual numbers in the absence of Japanese subsidies. The two approaches produce similar counterfactual changes across age bins, with the largest effects among vehicles aged 6–13 years. The similarity between the two approaches suggests that the counterfactual based on the DiD estimates provides a reasonable approximation to the aggregate effects of Japanese subsidies on first-time registrations through changes in prices. Table 6 decomposes the difference between the two approaches into components corresponding to the two concerns in Section 4. For each make, I remove the estimated effects of that make's subsidies on the landed prices of its products in all years, re-solve the equilibrium in each year, and compute

[41] The convergence tolerance is 10^{-5} for the maximum absolute difference between log demand and log supply across products. In the rare cases where j^+ is outside the choice set $\mathcal{J}_t$, I use an imputed price that is different across scenarios. Under the baseline age limit, I use the predicted price of j^+ from the same hedonic price regressions that impute missing prices for available products in the baseline, described in Appendix A, and adjust for the estimated price effects of subsidies in scenarios without subsidies. Under the lower age limit, products aged 14 and above that remain in the choice set are no longer importable, and their equilibrium prices may rise relative to those under the baseline age limit. To account for these price changes, I regress the log price ratios between the two age limits on age and make fixed effects, using available products aged 14 and above in both scenarios. I then apply the fitted ratios to the imputed prices of products outside the choice set under the baseline age limit. Because the fitted ratios depend on equilibrium prices, I iterate between the regression and the equilibrium solution until convergence.

[42] For products not active in 2023, missing product-level unobservables within the observed age range of a make-model are linearly interpolated across adjacent observed ages; outside the observed age range, the nearest observed value is carried forward.

only the resulting changes in that make's first-time registrations. I then sum these changes across makes for the model-implied effects of each make's own subsidies, holding other makes' subsidies fixed. Its difference from the aggregate effects estimated with the DiD approach corresponds to the first concern, that the DiD estimates may not recover the effects of each make's own subsidies. The difference between the aggregate effect estimated using the structural model and the model-implied effects of each make's own subsidies corresponds to the second concern, that the counterfactual based on the DiD estimates does not account for the effects of other makes' subsidies. Both differences are modest in magnitude compared with the aggregate effects estimated using the structural model, particularly among first-time registrations aged 6–13, where Japanese subsidies have the largest effects.



Notes: The figure compares the observed number of first-time registrations in Uganda between 2019 and 2023 with counterfactual numbers in the absence of Japanese subsidies. The DiD counterfactual removes the estimated age-bin-specific effects of subsidies from the observed numbers of first-time registrations. The structural counterfactual is from re-solving for the model's equilibrium in each year after removing the estimated effects of subsidies on landed prices.

Figure 3: The number of first-time registrations

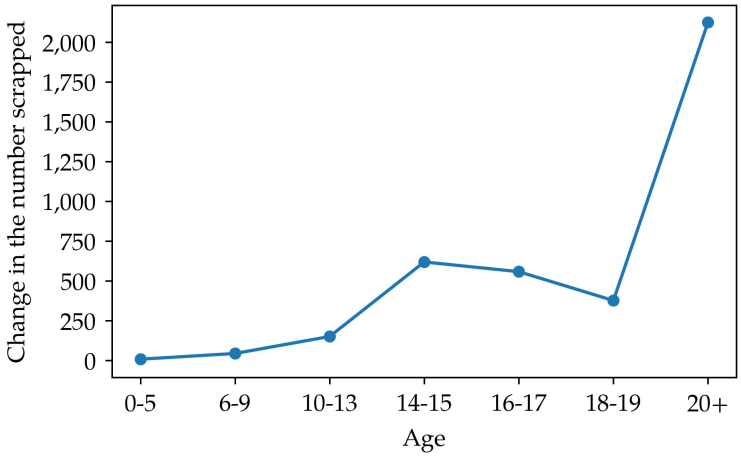
	Age				
	0–5	6–9	10–13	14–15	Total
DiD estimate	245	3,818	9,795	−467	13,391
+ Difference in the estimated effect of a make's own subsidies	159	927	3,076	−1,330	2,832
= Model-implied effect of a make's own subsidies	404	4,745	12,871	−1,797	16,223
+ Model-implied effect of other makes' subsidies	−98	−74	−341	−1,307	−1,820
= Structural estimate	306	4,671	12,530	−3,104	14,403

Notes: The DiD estimate, structural estimate, and model-implied effect of a make's own subsidies are all calculated as observed minus counterfactual numbers of first-time registrations over 2019–2023. For the DiD estimate, counterfactual numbers are constructed according to Equation (2). For the structural estimate, counterfactual numbers are constructed from adjusting observed landed prices according to Equation (11) and re-solving the equilibrium in each year. For the model-implied effect of a make's own subsidies, counterfactual numbers are computed one make at a time from adjusting only that make's prices, re-solving the equilibrium in each year, and isolating the resulting registrations of that make.

Table 6: Decomposition of the difference between the DiD and structural estimates of the effects of Japanese subsidies on first-time registrations

Overall, the structural model implies that Japanese subsidies increased first-time registrations by 13.08% over this period. The shift toward younger vehicles reduced average emissions per kilometer traveled among first-time registered vehicles by 0.96% for CO_2, 1.13% for NO_x, and 0.71% for particle number (PN).

Japanese subsidies also accelerated the scrappage of existing vehicles in Uganda. Figure 4 shows the model-implied changes in the number of vehicles scrapped in each age bin. Lower prices of first-time registered vehicles also reduced the domestic prices of other vehicles, increasing scrappage across all age bins. More than half of the additional scrapped vehicles are aged 20 years or older, suggesting that the additional imports of vehicles aged 6–13 years displaced mainly older vehicles. In total, the subsidies increased the number of vehicles scrapped between 2019 and 2023 by 4.40%.



Notes: The figure plots the model-implied change in the number of vehicles scrapped in Uganda from 2019 to 2023 under Japanese subsidies relative to a counterfactual without subsidies. The horizontal axis indicates the age at scrappage. The last age group pools ages 20 to 35, the terminal age in the model.

Figure 4: The effect of Japanese subsidies on scrappage

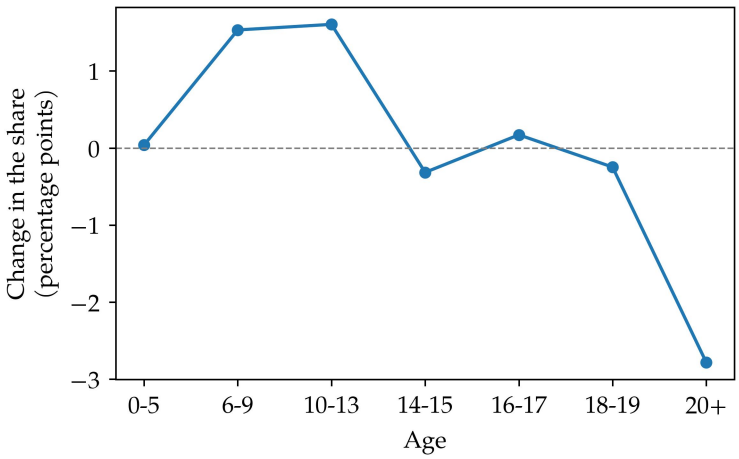
Despite the increase in scrappage, Japanese subsidies expanded the fleet in Uganda and shifted its composition toward younger and generally less emissions-intensive vehicles. By the end of 2023, the fleet was 4.45% larger than in the counterfactual without subsidies. Figure 5 shows the changes in its age distribution, with increases in the shares of vehicles aged 6–13 years and declines in the shares of older vehicles, particularly those aged 20 years and older. Consequently, the average age was 2.12% lower, and average emissions per kilometer traveled declined by 1.02% for CO_2, 2.43% for NO_x, and 1.94% for PN.

To compute changes in the annual emissions of each pollutant, I estimate annual kilometers traveled at each vehicle age, VMT_a, using the mileage reported in the online listings described in Section 3.2. I fit the mean mileage at each age from 1 to 35 as a quadratic function of age without a constant, using weighted least squares with weights equal to the number of listings. Figure A9 plots the mean mileage at each age and the fitted line. The annual kilometers traveled at age a are then calculated as the difference between fitted mean mileage at ages $a + 1$ and a. Emissions of

pollutant ℓ in year t and scenario ω are

$$E_{\ell t}^{\omega} = \sum_{j} M_{jt}^{\omega} VMT_{a(j)} e_{jt}^{\ell},$$

where M_{jt}^{ω} is the number of vehicles of product j on the road in year t and scenario ω, and e_{jt}^{ℓ} is the emissions of pollutant ℓ per kilometer traveled with product j in year t. Because a product is defined by a make, model, and age, the same product j corresponds to different manufacturing years across years, and can therefore have different per-kilometer emissions due to different emissions-control technologies. In the end, I find that Japanese subsidies increase emissions of CO_2, NO_x, and particulate matter in 2023 by 4.04%, 2.56%, and 3.07%. That is, the market expansion effect more than offset the composition effect, leading to an increase in total emissions.



Notes: The figure plots the model-implied percentage-point change in each age bin's share of Uganda's fleet at the end of 2023 under Japanese subsidies relative to a counterfactual without subsidies.

Figure 5: The effect of Japanese subsidies on the age distribution of the fleet

Finally, I estimate the effects of Japanese subsidies on welfare in Uganda. I measure welfare as discounted cumulative consumer surplus net of discounted cumulative emissions damages. The annual consumer surplus equals the gross value of vehicle services minus financing costs, repair costs, and expenditures on imported vehicles. Payments for domestic stocks in Uganda cancel out across consumers. Following Trajtenberg (1989), the value of vehicle services net of user costs in year t under scenario ω is

$$NVS_t^{\omega} = \mathcal{M}_t \int \frac{1}{\alpha} \log \left[1 + \sum_{m} D_{mt}^{\omega}(y)^{1-\sigma} \right] dF_t(y).$$

The gross value of vehicle services is NVS_t^{ω} plus user costs. Under the interpretation of $d(y)$ in Section 5, part of the user cost, $[\varrho - d(y)]R_{jt}^{\omega}$, reflects financing costs. The annual consumer surplus

is therefore

$$CS_t^\omega = NVS_t^\omega + \mathcal{M}_t \int \sum_j s_{jt}^\omega(y)\Big[\underbrace{r_{jt}^\omega(y)}_{\text{user cost}} - \underbrace{\big(\varrho - d(y)\big)R_{jt}^\omega}_{\text{financing cost}}\Big] dF_t(y) - \underbrace{\sum_j S_{jt}^\omega \bar{c}_{jt}^\omega}_{\text{repair costs}} - \underbrace{\sum_j N_{jt}^\omega \bar{p}_{jt}^\omega}_{\text{import expenditures}} .$$

The discounted cumulative consumer surplus from 2019 through year T is

$$CS_{2019:T}^\omega = \sum_{t=2019}^{T} \varrho^{t-2019} CS_t^\omega + \varrho^{T-2019} V_T^\omega,$$

where V_T^ω accounts for the remaining value of vehicles at the end of year T to consumers and is equal to

$$V_T^\omega = \varrho \sum_j M_{jT}^\omega R_{jT}^\omega.$$

Similarly, the discounted cumulative emissions damages from pollutant ℓ under scenario ω are

$$D_{\ell,2019:T}^\omega = \sum_{t=2019}^{T} \varrho^{t-2019} \tau_\ell E_{\ell t}^\omega,$$

where τ_ℓ is the monetary damage per unit of emissions of pollutant ℓ. Taken together, welfare under scenario ω is $W_{2019:T}^\omega = CS_{2019:T}^\omega - \sum_\ell D_{\ell,2019:T}^\omega$.

For the calculations, I set $T = 2028$, with the extended period allowing for the effects of changes in vehicle inflows to unfold over time. With subsidies, the fleet is 4.65% larger, and average emissions per kilometer are lower by 1.24% for CO_2, 2.29% for NO_x, and 2.05% for PN in 2028. Total emissions of CO_2, NO_x, and PN in that year are higher by 3.95%, 2.85%, and 3.11%. I consider NO_x and PN but not CO_2 when calculating emissions damages, as CO_2 emissions impose damages on Uganda regardless of their geographic origin, and additional emissions in Uganda may be offset through lower emissions in Japan. I set τ_{NO_x} to 15,138 in 2013 USD per metric ton, based on the monetary damage per unit of NO_x emissions recommended for evaluating transport projects in Uganda.[43] I set τ_{PN} to 9.96 million in 2013 USD per 10^{21} particles, based on estimated mortality attributable to particulate emissions from road transport in Uganda.[44]

Table 7 reports the effects of Japanese subsidies on welfare in Uganda. Over 2019–2028, Japanese subsidies increase both discounted cumulative consumer surplus and emissions damages, with

[43] See https://www.scribd.com/document/855402476/1-Road-Planning-Manual-Analysis-Report, last accessed October 2026.

[44] In the absence of direct estimates of mortality damages per particle in Uganda, I construct an estimate as follows. I estimate total mortality damages in 2019 attributable to particulate emissions from road transport as the product of 4,586 deaths from ambient $PM_{2.5}$ pollution in 2019 in Uganda (World Bank, 2022a), a value of statistical life of 468,000 USD for Uganda (Roy, 2016), and the 24% share of ambient $PM_{2.5}$ pollution in Kampala from road transport (Crowe et al., 2025). I then compute the monetary damage per particle as the ratio of total mortality damages to the total number of particles emitted in my sample in 2019. This estimate may be an underestimate because mortality related to $PM_{2.5}$ does not reflect all health effects of particulate pollution or an overestimate because it attributes pollution from all road transport to the light-duty passenger vehicles in my sample.

the increase in consumer surplus outweighing the additional emissions damages. Overall, the subsidies result in a net welfare gain of 92.23 million USD.

	With subsidies
Consumer surplus	+187.91
Environmental damages	+95.67
NO_x emissions (t)	+263.8
NO_x damages	+3.02
PN emissions (10^{21} particles)	+12.2
PN damages	+92.65
Welfare	+92.23

Notes: The table reports differences in outcomes over 2019–2028 with versus without Japanese subsidies under the 15-year import age limit. Monetary outcomes are in millions of 2013 USD and discounted to 2019. Changes in emissions are undiscounted cumulative totals over 2019–2028.

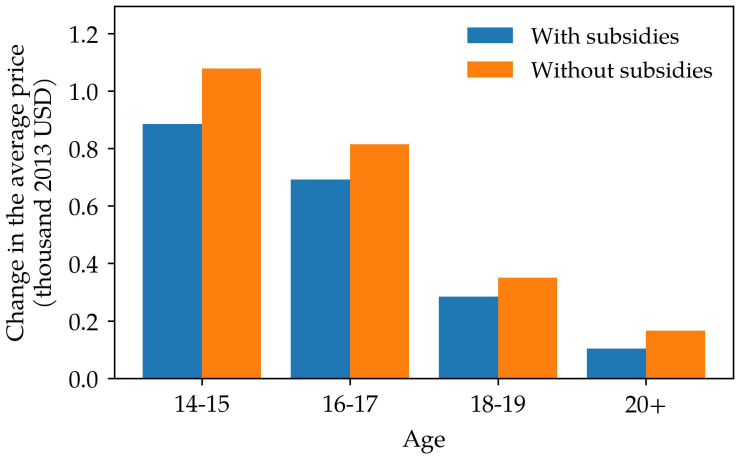
Table 7: The effects of Japanese subsidies on welfare

7.3 Implications for Designing Import Restrictions in Uganda

I next examine the interaction between Japanese subsidies and age-based import restrictions in Uganda. By shifting the age composition of vehicles entering Uganda, Japanese subsidies may affect the consequences of import restrictions that directly target the age. Given the recent proposal in Uganda to tighten its maximum import age from 15 to 13 years, I estimate the effects of this tighter limit and compare them with and without Japanese subsidies.

Tightening the age limit shrinks the set of importable products and raises domestic prices of products ineligible for import, reducing consumer surplus. Figure 6 shows that the tighter limit raises the prices of vehicles aged 14 years or older over 2019–2023, with the increases declining with age. Such a pattern reflects stronger substitution toward vehicles of similar ages to those aged 14–15 years, which become ineligible for import under the tighter limit. Moreover, prices increase less when Japanese subsidies are present, because younger vehicles that remain eligible for import are cheaper, encouraging consumers to choose them rather than older vehicles. These smaller price increases translate to 4.65% smaller decreases in consumer surplus, as shown in the first row of Table 8.

On the other hand, tightening the age limit reduces the size of the fleet, which in turn reduces emissions. Figure 7 shows that with Japanese subsidies, the tighter limit leads to smaller reductions in both the number of first-time registrations and the number of scrapped vehicles between 2019 and 2023. While consumers substitute toward younger vehicles under both scenarios, the lower prices of these vehicles with subsidies encourage more consumers to purchase cars, mitigating the decline in the number of first-time registrations. Meanwhile, the larger increases in domestic prices without subsidies lead to a greater reduction in the number of vehicles scrapped, as higher prices encourage owners to keep their vehicles. Nevertheless, the larger decline in the number of first-time registrations outweighs the greater reduction in the number of vehicles scrapped, resulting in a reduction in the fleet size that is 2,180 vehicles larger without subsidies.



Notes: The figure shows the change in the average price over 2019–2023 resulting from lowering the maximum import age from 15 to 13 years, with and without Japanese subsidies. In each scenario, the average prices are calculated across make × model × age × year cells with cars on the road and available prices in all four scenarios, with weights being the numbers of cars on the road under the 15-year limit with subsidies.

Figure 6: The effect of the 13-year age limit on the average price

	With subsidies	Without subsidies
Consumer surplus	−201.81	−211.65
Environmental damages	−175.70	−240.20
NO_x emissions (t)	−627.4	−806.8
NO_x damages	−6.87	−8.89
PN emissions (10^{21} particles)	−20.9	−28.3
PN damages	−168.83	−231.31
Welfare	−26.11	+28.55

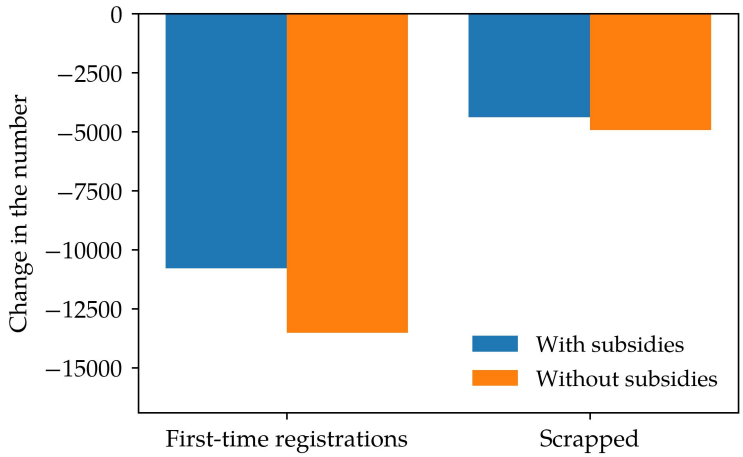
Notes: The table reports differences in outcomes over 2019–2028 from lowering the maximum import age from 15 to 13 years in Uganda, with and without Japanese subsidies. Each difference is the outcome under the 13-year limit minus that under the 15-year limit, holding subsidies fixed. Monetary outcomes are in millions of 2013 USD and discounted to 2019. Changes in emissions are undiscounted cumulative totals over 2019–2028.

Table 8: The effects of the 13-year age limit on welfare with versus without Japanese subsidies

In addition, tightening the age limit shifts the composition of the fleet toward less emissions-intensive vehicles, further reducing emissions. Figure 8 shows that the tighter limit reduces average NO_x and particulate emissions per kilometer traveled more with Japanese subsidies than without them, again reflecting greater substitution toward younger and less emissions-intensive vehicles given their lower prices with Japanese subsidies.

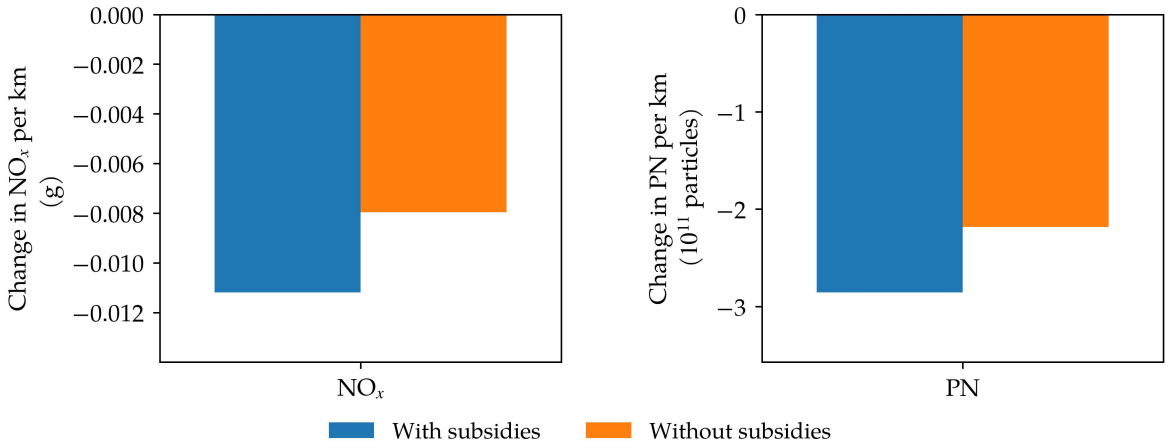
Over the longer horizon of 2019–2028, the reductions in total NO_x and particulate emissions from the tighter age limit are 22.24% and 26.15% smaller with Japanese subsidies than without them, according to estimates in Table 8. The tighter limit produces larger reductions in emissions per kilometer with subsidies, but the smaller reduction in the fleet size dominates these improvements. This echoes the finding in the previous subsection that Japanese subsidies expand the fleet sufficiently to increase total emissions despite lowering emissions per kilometer.

Ultimately, tightening the import age limit reduces welfare by 26.11 million USD with subsidies



Notes: The figure shows the changes in the total number of first-time registrations and cars scrapped in Uganda over 2019–2023 resulting from lowering the maximum import age from 15 to 13 years, with and without Japanese subsidies.

Figure 7: The effect of the 13-year age limit on first-time registrations and scrappage



Notes: The figure shows the change in average NO_x and particle number (PN) emissions per kilometer of cars on the road over 2019–2023 resulting from lowering the maximum import age from 15 to 13 years, with and without Japanese subsidies. In each scenario, average emissions per kilometer are calculated across make × model × age × year cells with cars on the road, with weights being the numbers of cars on the road in that scenario.

Figure 8: The effect of the 13-year age limit on emissions per kilometer

but increases welfare by 28.55 million USD without them, as shown in the last row of Table 8. Though the net effects depend on the assumed monetary damages from emissions, the conclusion that the tighter limit requires larger monetary benefits per unit of emissions reduced to be welfare-improving with subsidies than without them is robust to these assumptions. With subsidies, the break-even values of τ_{NO_x} and τ_{PN} are 1.15 (= 201.81/175.70) times their assumed benchmarks, compared with 0.88 (= 211.65/240.20) times without subsidies, a difference of 30.4%. The reversal in net effects therefore does not hinge on a particular choice of monetary emissions damages, but persists over a wide range of estimates.

8 Conclusion

Environmental policies in exporting countries can have consequences beyond their borders, particularly when regulated goods are subsequently traded in international secondary markets. This paper studies such spillovers in the context of Japan's clean vehicle subsidies and Uganda. I find that Japanese subsidies lower prices and increase the number of first-time registered vehicles in Uganda, particularly among relatively young and less emissions-intensive ones. Consequently, consumer welfare increases, but so do total emissions, as the expansion of the fleet outweighs reductions in emissions per kilometer. These findings suggest that failing to account for leakages through international used-vehicle trade may overstate the global environmental benefits of clean vehicle policies. I also show that environmental policies abroad can change the tradeoff between consumer welfare and emissions damages associated with domestic environmental regulations. In particular, Japanese subsidies make Uganda's proposed tightening of its import age limit less cost-effective.

Several extensions of this paper could be explored in future research. First, this paper focuses on the short-run replacement channel, through which subsidies encourage Japanese consumers to replace existing vehicles and the replaced vehicles become additional supply of used vehicles available for export. Over longer horizons, subsidies may also change used-vehicle exports through changes in the composition of new vehicles entering Japan's fleet, which reach the used-vehicle market years after. Second, vehicles imported into Uganda are relatively old, averaging more than 15 years during the sample period. In countries importing younger vehicles,[45] the effects of foreign clean vehicle policies on fleet dynamics, emissions, and overall welfare may be different. For example, differences in the extent to which additional imports are less emissions-intensive than the existing fleet can change the composition effect.

More broadly, many other goods, such as airplanes, are actively traded in global used-goods markets, oftentimes from developed to developing countries. Similar to clean vehicle policies, there is extensive evidence that environmental policies for these goods are effective in facilitating local clean transitions,[46] but relatively little is known about their international spillovers through used-goods trade. The findings in this paper suggest that such spillovers can be substantial, and that importing countries should account for them when designing domestic environmental regulations.

[45] For example, based on registration records from the NZ Transport Agency Waka Kotahi, used vehicles from Japan were around 9 years old on average when first registered in New Zealand between January 2020 and October 2025.

[46] For example, see De Jong (2022) for the effects of emissions pricing on airplane retirement in the EU.

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A Data Construction Details

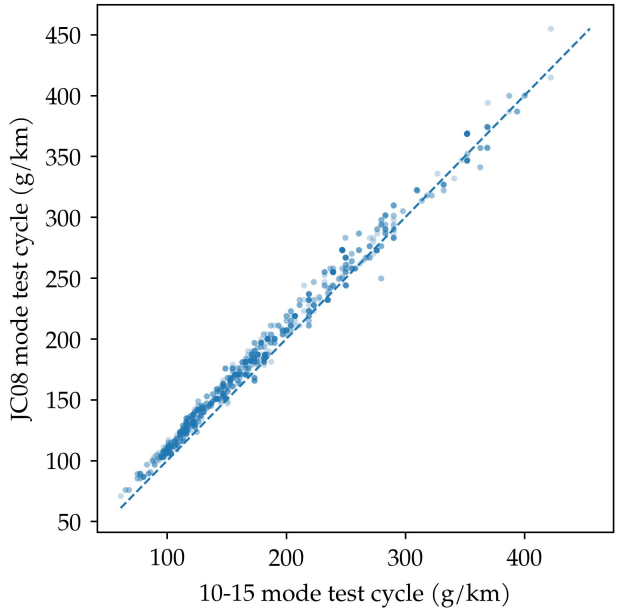
A.1 CO_2 emissions

I combine data on CO_2 emissions from Gazoo and the Japanese Ministry of Land, Infrastructure, Transport and Tourism (MLIT). MLIT reports the years in which each variant is listed for sale as new in Japan, while Gazoo reports model years and each generation's end year. To assign CO_2 emissions to each variant and year of sale, I thus forward-fill emissions from Gazoo for each variant until the next reported model year or its generation ends, while using emissions from the MLIT only for their reported years.

Test cycles Fuel economy in Japan has been measured under three standardized test cycles: the 10–15 mode, the JC08 mode, and the Worldwide Harmonized Light Vehicles Test Cycle (WLTC), with gradual transitions from the 10–15 mode to JC08 beginning in 2005 and from JC08 to WLTC beginning in 2018. For each variant, the MLIT reports both fuel economy measurements and CO_2 emissions per kilometer converted from them, while Gazoo reports only fuel economy measurements. I convert CO_2 emissions per kilometer from the MLIT and fuel economy measurements from Gazoo to their JC08 equivalents, using conversion relationships estimated separately for the two data sources. Fuel economy measurements under different test cycles, as well as the corresponding CO_2 emissions per kilometer, exhibit approximately linear relationships, as illustrated in Figure A1 for CO_2 emissions per kilometer from MLIT. I therefore estimate linear conversion relationships using variants with measurements reported under two test cycles in the same year. In the data from the MLIT, regressing JC08 CO_2 emissions on 10–15 CO_2 emissions yields an intercept of 13.7 and a slope of 0.978 (1,094 variant-years, $R^2 = 0.99$), while regressing JC08 emissions on WLTC emissions yields an intercept of −13.6 and a slope of 0.954 (1,854 variant-years, $R^2 = 0.96$). For data from Gazoo, I estimate analogous regressions using fuel economy measured in km/L. The regressions of JC08 fuel economy on 10–15 and WLTC fuel economy yield slopes of 0.866 and 1.347, respectively (2,745 and 6,816 variant-years, with R^2 values of 0.99 and 0.94). I retain reported JC08 CO_2 emissions from MLIT and JC08 fuel economy measurements from Gazoo when available, and apply the estimated conversions otherwise. I additionally convert the standardized JC08 fuel economy measurements from Gazoo to CO_2 emissions per kilometer using fuel-specific emission factors.

Imputations The imputation procedure assumes a common time trend in CO_2 emissions across make–model pairs, while allowing make-model pairs with observed CO_2 emissions to have their own observed levels and make-model pairs without direct observations to share the level of the most narrowly defined comparable group. In particular, I consider the following regression of log CO_2 emissions on make–model fixed effects and a linear trend in model year:

$$\log e_{make,model,t} = \eta_{make,model} + g(t) + \varepsilon_{make,model,t},$$



Notes: Each dot represents a vehicle variant in a given manufacturing year between 2014 and 2024 for which MLIT reports CO_2 emissions under both test cycles.

Figure A1: CO_2 emissions measured with different testing cycles

where $g(t) = b(t - 2000)$. The linear trend reflects technological improvements across model years. I estimate the regression using 6,913 observations from Gazoo. Each observation is the average CO_2 emissions among the variants that a make and model releases in a model year. The estimated coefficient is $\hat{b} = -0.0199$ ($R^2 = 0.93$), suggesting a decline in CO_2 emissions of approximately 2 percent per model year. This linear trend closely tracks more flexibly estimated time trends, such as the one from an alternative specification with separate fixed effects for each vehicle model year, as shown in Figure A2.

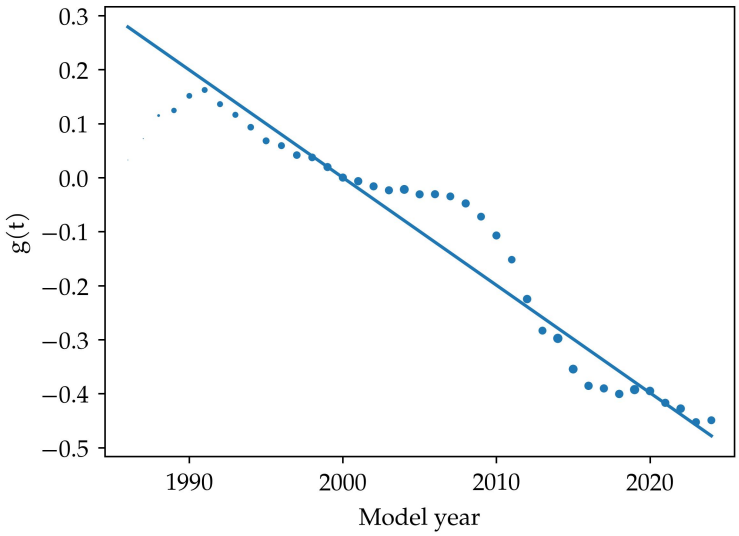
For make–model pairs with observed average CO_2 emissions across variants in at least one year through 2024, I use the estimated common trend to impute missing emissions. Let t° denote the model year through 2024 closest to t in which the make–model pair has observed CO_2 emissions, taking the earlier one when two are equally close. I impute the missing CO_2 emissions for model year t as

$$\widehat{e}_{make,model,t} = e_{make,model,t^\circ} \exp\left\{\widehat{g}(t) - \widehat{g}(t^\circ)\right\}.$$

For make–model pairs without observed average CO_2 emissions across variants, I impute emissions as

$$\widehat{e}_{make,model,t} = \exp\left\{\widehat{\eta}_{k(make,model)} + \widehat{g}(t)\right\},$$

where $k(make, model)$ denotes the most narrowly defined comparable group with observed CO_2 emissions. I consider the following groups in sequence: make × segment, make × body type, segment, body type, and the full sample. For each group, I hold the estimated common trend $\widehat{g}(t)$ fixed and estimate the group effect η_k as the average detrended log CO_2 emissions among observed



Notes: Each dot represents the estimated fixed effect for a model year from a regression of log CO_2 emissions on make × model fixed effects and separate fixed effects for each model year. The reference year is 2000. The sample includes average CO_2 emissions for each make, model, and model year between 1986 and 2024 observed from Gazoo. Dot sizes are proportional to the number of make–model pairs with observed CO_2 emissions in the corresponding model year. The line represents the estimated linear trend from a regression using the same data and make × model fixed effects but replacing the year fixed effects with a linear trend.

Figure A2: The change in the average CO_2 emissions across model years

make-model pairs in that group:

$$\widehat{\eta}_k = \frac{1}{N_k} \sum_{(make,model,t)\in k} \left[\log e_{make,model,t} - \widehat{g}(t)\right].$$

I apply the same imputation procedure to the post-sample period, for which CO_2 emissions of model years after 2024 are imputed using the estimated common trend and observed emissions through 2024.

Of all first-time registered vehicles from January 2000 through June 2024 that were no older than 35 at some point between 2019 and 2024, 90.8 percent have directly observed CO_2 emissions, while 4.3 percent belong to make–model pairs with observed emissions in another model year. For the remaining vehicles, CO_2 emissions are imputed at the make × segment level (3.5 percent), make × body-type level (0.8 percent), segment level (0.4 percent), body-type level (0.2 percent), and full-sample level (0.0 percent).

A.2 Local Pollutant Emissions

I first construct NO_x and particulate emissions of new vehicles using emissions certification codes from Gazoo and MLIT. I then account for age-related deterioration to estimate emissions of used vehicles using on-road emissions measurements from Crowe et al. (2025).

A.2.1 Emissions of New Vehicles

NO_x emissions Gazoo and MLIT report the emissions certification code of each variant. The code indicates the applicable emissions regulation year and the extent to which the variant's certified emissions fall below the regulatory limits, in bands of 25, 50, and 75 percent (the "stars" of Japan's low-emission vehicle labeling). MLIT publishes certified NO_x emissions in grams per kilometer for some certification codes. For the remaining codes, I derive certified emissions from the applicable regulatory limits based on the regulation year, certification band, fuel type, and category (e.g., passenger car).

Test cycles Local pollutant emissions in Japan are certified under the same three test cycles as CO_2 emissions: the 10–15 mode, JC08, and WLTC. Each variant has a single emissions certification code, which determines its certified emissions under one test cycle. I define the test cycle associated with each emissions certification code based on its applicable regulation year. Specifically, I assume that codes corresponding to regulations before 2005 are certified under the 10–15 mode, those from 2005 to 2017 under JC08, and those from 2018 onward under WLTC. I convert certified NO_x emissions to their JC08 equivalents, as for CO_2 emissions. The relationships between certified NO_x emissions under different test cycles are approximately linear, like with CO_2 emissions, so I estimate linear conversions separately for Gazoo and MLIT. Both Gazoo and MLIT report the seven-digit model code associated with each variant. For each model code certified under both test cycles, I average certified emissions separately for each cycle. Each average includes observations from years within one year of at least one observation under the other cycle. The transition from the 10–15 mode to JC08 coincided with a tightening of the NO_x emissions limits in 2005. For variants remaining in the same certification band, this tightening mechanically reduces computed certified emissions even when their actual emissions remain unchanged. To reduce the influence of this mechanical change on the estimated conversion from the 10–15 mode to JC08, I additionally restrict the sample to variants whose certified percentage reduction below the regulatory limit is smaller under JC08 than under the 10–15 mode. The estimated relationships are JC08 NO_x = 0.0086 + 0.804× 10–15 NO_x for Gazoo (217 model codes, R^2 = 0.75) and JC08 NO_x = 0.0154 + 0.565× 10–15 NO_x for MLIT (210 model codes, R^2 = 0.70). For the conversion from WLTC to JC08, I do not impose the additional restriction because the NO_x emissions limits are the same under both cycles. The estimated relationships are JC08 NO_x = 0.0026 + 0.512× WLTC NO_x for Gazoo (298 model codes, R^2 = 0.76) and JC08 NO_x = 0.0023 + 0.536× WLTC NO_x for MLIT (352 model codes, R^2 = 0.84).

Particulate emissions The emissions certification code also provides information about each variant's engine and emissions-control technologies. However, Japan's emissions certification standards regulate particle mass rather than particle number. To have estimates of the number of particles emitted that are comparable to the on-road measurements in Crowe et al. (2025), I use emissions tests from fiscal year 2015 that Japan's Ministry of the Environment reports. The tests measure the number of particles emitted from nearly new light-duty passenger vehicles with

different engine and emissions-control technologies.[47] I use the median measured emissions for each engine and emissions-control technology, which are equal to 1.1×10^{11} particles per kilometer for port-injection gasoline engines, 1.3×10^{12} for direct-injection gasoline engines, and 1.8×10^{9} for diesel engines with particle filters. I scale the median measured particulate emissions for each engine and emissions-control technology to have variant-specific emissions. The scaling factor is the ratio of the variant's certified NO_x emissions to the median certified NO_x emissions of the tested vehicles with the same engine and emissions-control technology (0.0125 g/km for port-injection gasoline engines, 0.0125 g/km for direct-injection gasoline engines, and 0.08 g/km for diesel engines with particle filters). While all gasoline variants in Gazoo and MLIT are equipped with emissions-control technologies, this is not the case for diesel variants. In particular, all diesel variants certified under regulations before 2005 and a small number certified under the 2005 regulation do not have particle filters. I therefore assign these variants the particulate emissions level estimated below for fully deteriorated diesel engines, regardless of their age.

Imputations I combine average emissions across variants for each make, model, and year of sale from Gazoo and MLIT, and impute missing emissions following the same procedure as for CO_2 emissions in Appendix A.1. The only difference is that I allow the cohort trend $g(t)$ to be piecewise linear, with changes in slope in 2000, 2005, and 2009 to account for the tightening of NO_x emissions limits in those years. I estimate the cohort trend using 8,623 make-model-year averages of certified NO_x emissions from Gazoo, covering 993 make-model pairs over model years 1986–2024. The estimated slopes are -0.047 per year before 2000, -0.321 between 2000 and 2005, -0.071 between 2005 and 2009, and -0.0090 after 2009. For particulate emissions, I estimate a separate cohort trend using the same procedure, with estimated slopes of -0.037 before 2000, -0.319 between 2000 and 2005, -0.081 between 2005 and 2009, and -0.031 after 2009. For years after 2024, I extrapolate the cohort trends using their estimated post-2009 slopes.

Of all first-time registered vehicles from January 2000 through June 2024 that were no older than 35 at some point between 2019 and 2024, 94.2 percent have directly observed certified NO_x emissions, while 1.4 percent belong to make–model pairs with observed emissions in another model year. For the remaining vehicles, NO_x emissions are imputed at the make × segment level (3.1 percent), make × body-type level (0.8 percent), segment level (0.4 percent), body-type level (0.1 percent), and full-sample level (0.0 percent). The corresponding coverage shares for particulate emissions differ from those for NO_x emissions by no more than 0.3 percentage point.

A.2.2 Emissions of Used Vehicles

NO_x emissions The average certified NO_x emissions rise 11-fold from the 15–19 age group to the 30+ age group, while the average on-road NO_x emissions computed with data from Crowe et al. (2025) rise only 1.6-fold. This suggests that differences in certified emissions across manufacturing years become less important as vehicles age. I therefore assume that vehicles without functioning

[47] The emissions tests were conducted in fiscal year 2015 and their results are reported in materials from the 60th (2017) meeting of Japan's Central Environment Council's Motor Vehicle Emissions Expert Committee. See https://www.env.go.jp/council/07air-noise/y072-60/900426955.pdf for details, last accessed November 2026.

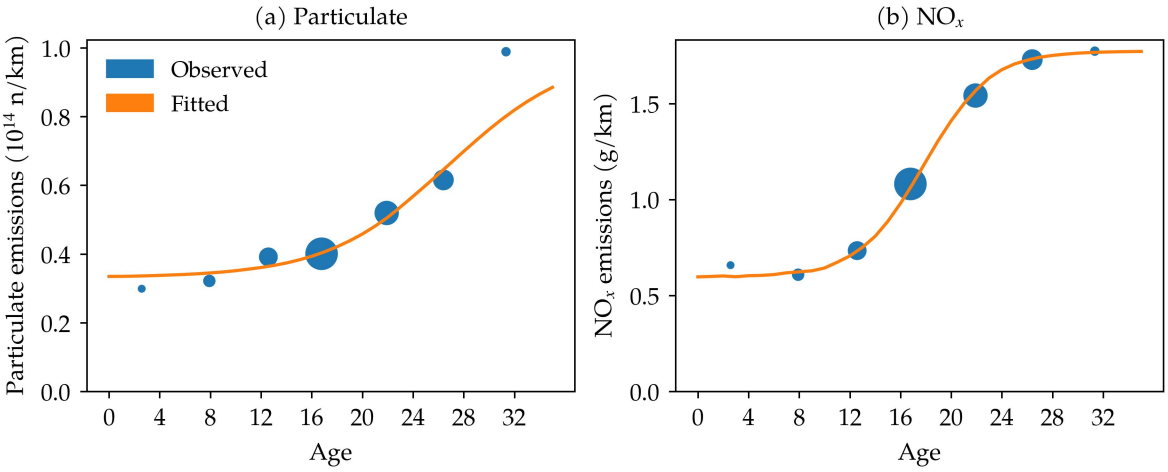
emissions-control equipment emit NO_x at a common level E, regardless of their certified emissions. I model average on-road NO_x emissions for vehicles of a given make, model, manufacturing year, and age as a weighted average of their certified emissions level e_j^0 and the common emissions level E:

$$NO_x(j,a) = S(a)E + \{1 - S(a)\}e_j^0, \qquad S(a) = \rho + (1-\rho)\frac{1}{1+\exp\{-(a-m)/s\}},$$

where $S(a)$ is the share of vehicles of age a without functioning emissions-control equipment. It consists of a constant fraction ρ of vehicles whose emissions-control equipment is assumed to have been removed upon entering Uganda, and a fraction of the remaining vehicles whose emissions-control equipment has failed with age, following a logistic curve with midpoint m and spread s. I set E to the mean on-road NO_x emissions of the oldest age group in Crowe et al. (2025), so that $\hat{E} = 1.77$ g/km. To estimate (ρ, m, s), I use the fleet as of July 2024 implied by the estimated model in Section 5. For each candidate vector of (ρ, m, s), I calculate predicted mean on-road NO_x emissions within each age group of this fleet. I estimate (ρ, m, s) by minimizing the sum of squared differences between the logarithms of predicted and observed mean on-road NO_x emissions across the seven age groups in Crowe et al. (2025). The weights are the number of vehicles included in the on-road emissions tests for each age group. The estimates are $\hat{\rho} = 0.32$ (s.e. 0.01), $\hat{m} = 17.8$ years (s.e. 0.1), and $\hat{s} = 2.7$ years (s.e. 0.2).[48] The implied share of vehicles without functioning emissions-control equipment is 0.32 at age 0, 0.49 at age 15, 0.79 at age 20, and 0.96 at age 25. The predicted mean on-road NO_x emissions closely match the observed age-group means, as shown in Panel (b) of Figure A3. I assign the predicted mean on-road NO_x emissions for each make, model, manufacturing year, and age to all vehicles with those characteristics.

Particulate emissions For particulate emissions, I use the same model and estimation procedure as for NO_x. I set E to 9.9×10^{13} particles per km, the mean on-road PN emissions of vehicles aged 30 years or older in Crowe et al. (2025). The estimates are $\hat{\rho} = 0.33$ (s.e. 0.04), $\hat{m} = 27.0$ years (s.e. 1.1), and $\hat{s} = 4.8$ years (s.e. 1.4). The implied share of vehicles without functioning emissions control is 0.34 at age 0, 0.39 at age 15, 0.60 at age 25, and 0.89 at age 35. The predicted mean on-road particulate emissions generally match the observed age-group means, as shown in Panel (a) of Figure A3. I assign the predicted mean on-road PN emissions for each make, model, manufacturing year, and age to all vehicles with those characteristics.

[48] Estimating E as well gives $\hat{E} = 1.76$ g/km (s.e. 0.04) and only changes the average on-road NO_x emissions of the July 2024 fleet by 0.1 percent.



Notes: The dots show mean on-road particulate number (panel a) and NO_x (panel b) emissions per kilometer for passenger vehicles in seven age groups, calculated using the 3,283 vehicles sampled by Crowe et al. (2025). Dot sizes are proportional to the number of sampled vehicles in each age group. The orange line plots the predicted mean emissions for each age in the model-implied July 2024 fleet.

Figure A3: Predicted on-road emissions

A.3 Prices

For each make, model, exact age, and quarter, I use the average listed price when available and impute missing prices using hedonic regressions described below. I then average the four quarterly prices to have annual prices for structural estimation.

Imputations For 2019 onward, I impute missing quarterly prices using a hedonic regression on observed quarterly prices. I first subtract the estimated age-bin-specific effects of Japanese subsidies from observed quarterly prices, using the estimates in Column (6) of Table 4, and then estimate a hedonic regression on the adjusted prices of make–model pairs. I restrict the sample to make–model pairs that are observed at three or more distinct ages. The regression includes make–model-specific linear age profiles, year-specific piecewise-linear age profiles, segment-year fixed effects, and quarter fixed effects. The make–model-specific age profiles are linear in age, while the year-specific age profiles are piecewise-linear. The age profiles all include an intercept. I normalize the make–model-specific intercepts to average zero within each segment and the year-specific age profiles to average zero across years. For missing quarterly prices of make–model pairs included in the regression, I use the corresponding fitted values. For other pairs, I use the unweighted average of the estimated age profiles among other models of the same make, or the same segment if none are available. If neither the same make nor the same segment has estimated age profiles, I use the unweighted average across all make–model pairs. I then combine these average age profiles with the year-specific age profiles, segment-year fixed effects, and quarter fixed effects. Finally, I add the estimated effects of subsidies back to obtain imputed prices.

For years before 2019, I follow a similar imputation procedure, but account for the more limited coverage of historical price listings and the lack of data on Japanese Clean Energy Vehicle subsidies before 2011. I estimate a separate hedonic regression using observed prices that (1) belong to

make–model pairs that are observed at three or more distinct ages and (2) belong to combinations of make and age bin with sufficient variation over time to identify their linear time trends. The regression includes make–model-specific linear age profiles, make-age-bin fixed effects, linear time trends specific to each combination of make and age bin, and quarter fixed effects. I normalize the make-age-bin fixed effects to average zero within each make. These time trends allow prices to be extrapolated to years without observed listings and can also reflect differences in the effects of Japanese subsidies across makes and over time. For missing quarterly prices of combinations of make, model, and age bin represented in the regression, I use the fitted values. For other combinations, I use the unweighted average of the estimated age profiles among other models of the same make, or the same segment if none are available. If neither the same make nor the same segment has estimated age profiles, I use the unweighted average across all make–model pairs. For combinations of make and age bin without estimated fixed effects or time trends, I use the unweighted average of the corresponding estimates across all makes for that age bin. I then combine the resulting age profiles, make-age-bin fixed effects, time trends, and quarter fixed effects to obtain imputed prices.

B Supplementary Descriptive Statistics

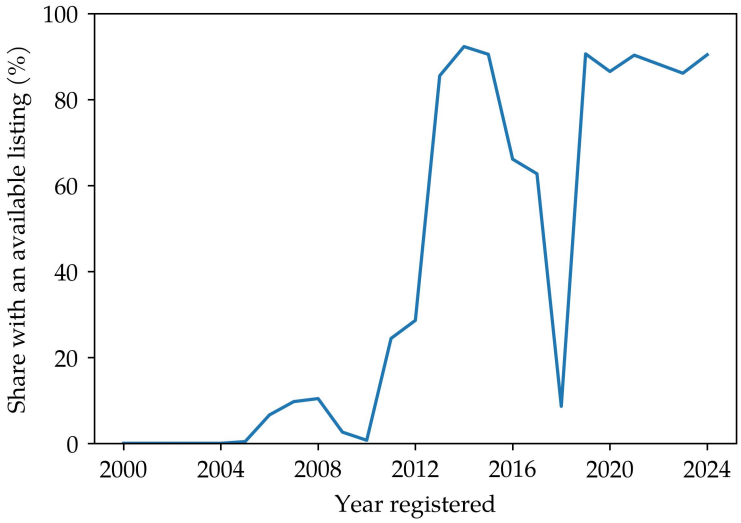
Make	Total	Share (%)	Mean age
Toyota	139,934	77.7	11.52
Mitsubishi	9,540	5.3	10.58
Nissan	5,642	3.1	10.98
Mercedes-Benz	5,339	3.0	10.94
Suzuki	3,542	2.0	11.04

Notes: The statistics are based on first-time registration records from 2000 through 2012 from Mutenyo et al. (2015), which do not report the country of export. Share is the make's share of all first-time registrations over the period. Mean age is the average of the year registered minus the year manufactured.

Table A1: Top five makes among first-time registered vehicles in Uganda

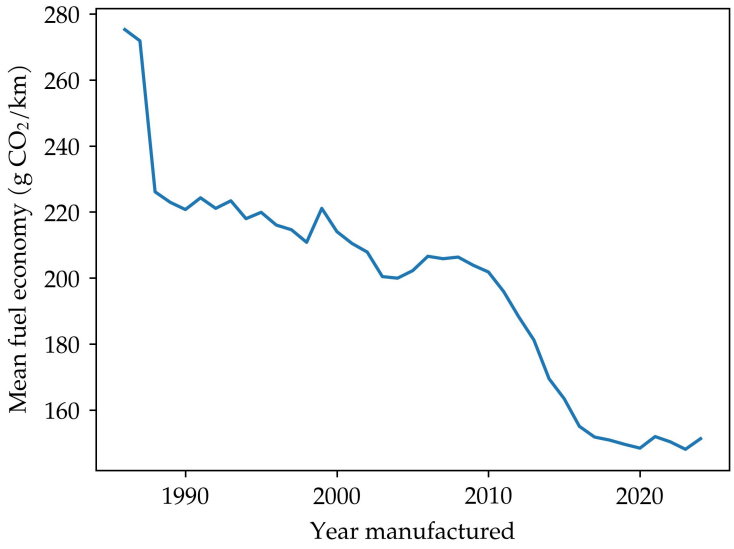
Platform	The number of listings	Years archived
cheki.co.ug	486,529	2010–2015
jiji.ug	103,859	2019–2024
autochek	79,787	2022–2024
cars.co.ug	34,464	2005–2024

Table A2: Online platforms providing listings in Uganda



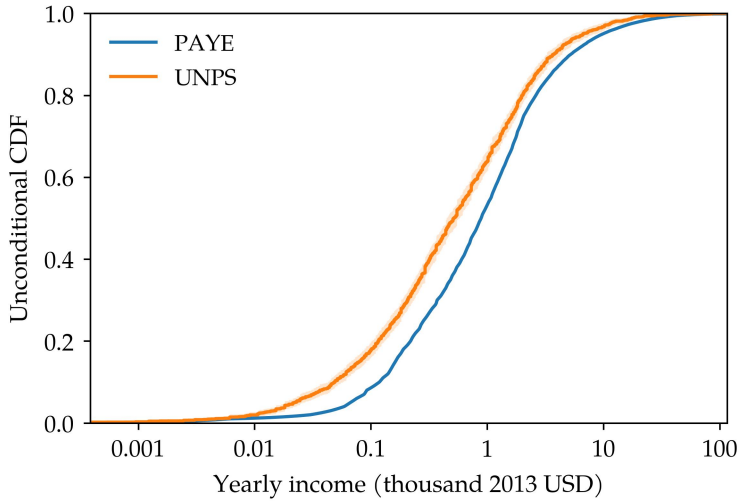
Notes: The figure plots the share of first-time registrations for which at least one listing is available with the same make, model, year of manufacture, and year of registration. Listings are dated using their posting dates when available and their archive dates otherwise.

Figure A4: Share of first-time registrations with an available listing



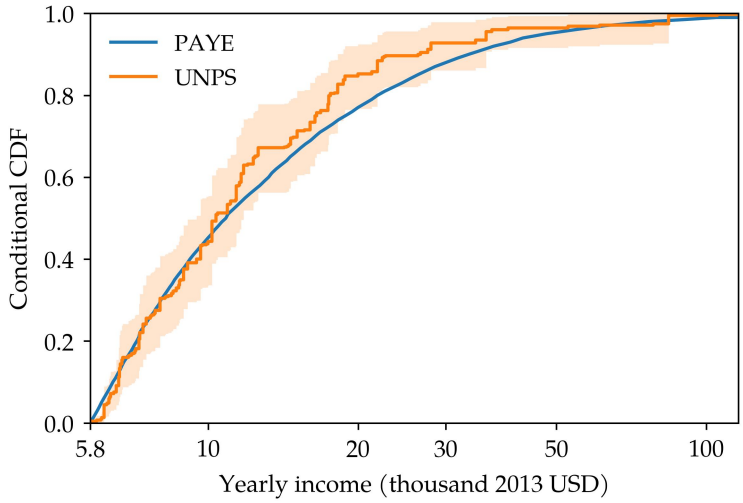
Notes: The figure plots, for each year manufactured from 1986 to 2024, the average CO_2 emissions per kilometer across variants with reported fuel economy from Gazoo. Fuel economy is converted to the JC08 test-cycle basis as described in Appendix A.1, and CO_2 emissions are calculated using emission factors of 2,348 grams per liter for gasoline and 2,689 grams per liter for diesel. Fuel type is identified from each variant's emissions certification code.

Figure A5: Mean CO_2 emissions



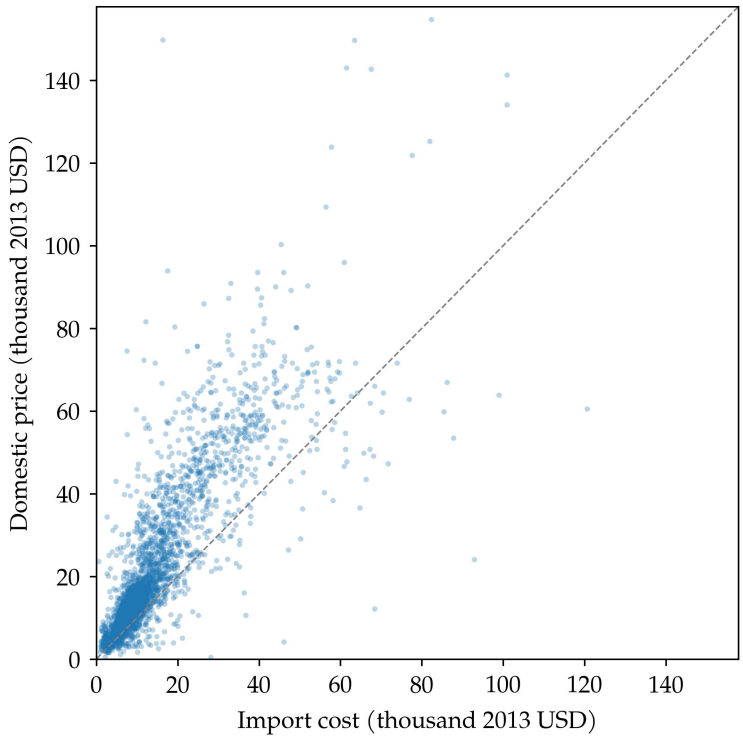
Notes: The blue curve plots the cumulative distribution function (CDF) of the annual income in 2019 for all individuals with positive income in the Uganda Revenue Authority's Pay As You Earn (PAYE) records. The orange curve plots the CDF of the annual income for individuals aged 20 or older with positive income in the 2019/20 Uganda National Panel Survey (UNPS). The income from PAYE is the sum of monthly gross earnings across all employers. The income from UNPS is the sum of wages, non-agricultural self-employment income, and agricultural income over the preceding 12 months. Individuals in the UNPS are weighted using household sampling weights to account for differences in the probability of households being selected into the survey. The horizontal axis is on a log scale. The shaded area is the 95% confidence band from bootstrap samples of individuals. The shaded area around the CDF from PAYE is barely visible.

Figure A6: Unconditional income distributions



Notes: The figure plots the cumulative distribution functions in Figure A6 conditional on annual incomes of at least 15 million 2013 UGX, the threshold used to define market sizes in Section 6. The horizontal axis is on a log scale. The shaded area is the 95% confidence band from bootstrap samples of individuals. The shaded area around the CDF from PAYE is barely visible.

Figure A7: Conditional income distributions



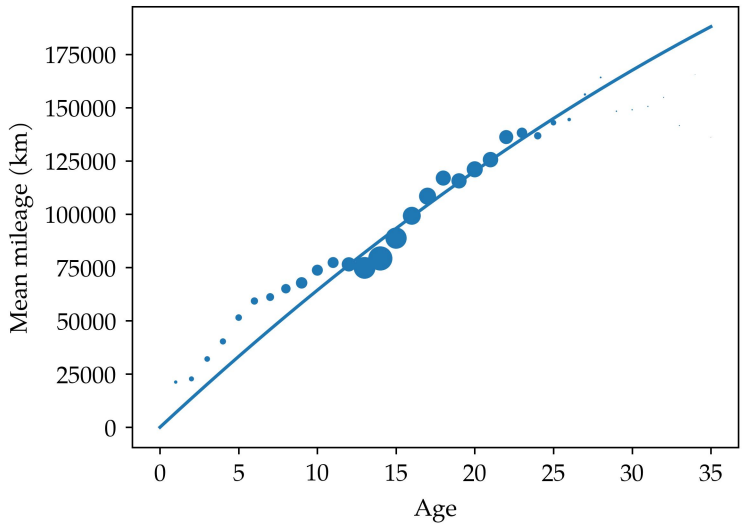
Notes: Each point represents a quarter registered×make×model×year manufactured from the first quarter of 2019 through the second quarter of 2024. The domestic price is the average listed price among the listings dated to the quarter. The import cost is the average customs value plus taxes and fees among the registrations in the cell. Both are in thousand 2013 USD. The dashed line is the 45-degree line.

Figure A8: Relationship between the domestic price and import cost

	Log import cost	
	(1)	(2)
Matched to a price	-0.268***	-0.006
	(0.022)	(0.004)
Make×Model×Age FE		✓
Age×Year FE		✓
Segment×Year FE		✓
Quarter FE		✓
R^2	0.052	0.929
Observations	123,244	122,001

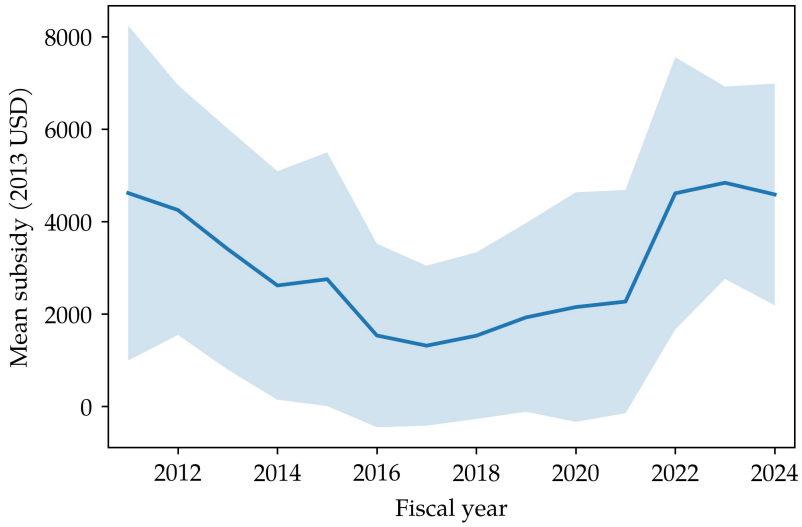
Notes: Each observation is a first-time registration from January 2019 through June 2024. The dependent variable is the log of the import cost, defined as the customs value plus taxes and fees, in 2013 USD. Column (2) drops singleton fixed effects. Standard errors clustered by make, model, year manufactured, and quarter registered in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A3: Import costs of cars matched and unmatched to a price



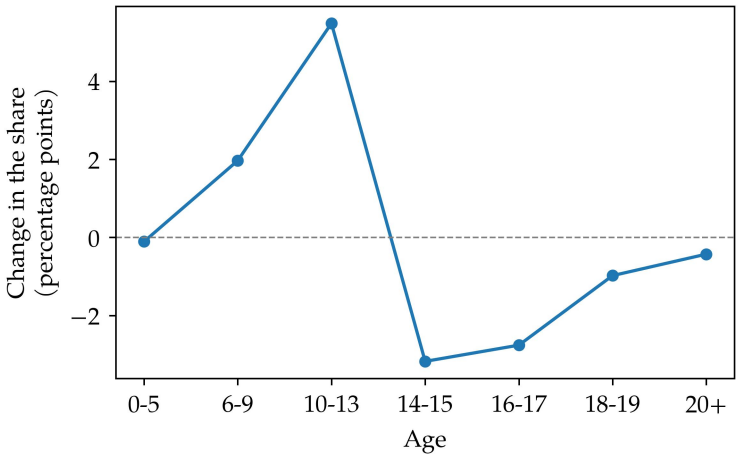
Notes: Each dot is the mean odometer reading of light-duty passenger vehicles listed for sale in Uganda at a given age, where age is the listing year minus the year of manufacture. The area of each dot is proportional to the number of listings at that age. The line is a second-order polynomial in age without a constant, estimated with weighted least squares on the age means and each age weighted by its number of listings.

Figure A9: Mean mileage



Notes: The figure plots, for each fiscal year from 2011 to 2024, the mean Japanese Clean Energy Vehicle (CEV) subsidy across all eligible light-duty passenger car variants, in 2013 USD. Fiscal years run from April to the following March. The shaded area represents one standard deviation above and below the annual mean.

Figure A10: Mean subsidies over time



Notes: The figure plots, for each age bin, the difference between the share of observed first-time registrations in Uganda from January 2013 through June 2024 and the model-implied share of counterfactual first-time registrations in the absence of Japanese subsidies, in percentage points. Counterfactual numbers of first-time registrations are computed according to Equation (2).

Figure A11: Subsidy-induced change in each age bin's share of first-time registrations

C Theoretical Foundations of the Structural Model

C.1 Microfoundation for the Heterogeneous Discount Factor

In this appendix, I present a simple model of borrowing that provides a microfoundation for the income-dependent discount factor $d(y_i)$ in Section 5. Lower borrowing costs allow richer consumers to place greater value on future cash, without requiring differences in the marginal utility of current consumption.

Consider consumer i with income y_i in market t. Suppose that the consumer finances marginal increases in current spending through borrowing and repays loans using cash received at the beginning of the following year. Financiers are competitive and risk-neutral, discounting future receipts by a common factor $\varrho = 0.95$. Lending an amount A to a consumer with income y incurs an additional cost $\tau_t(y)A$ in period t, where $\tau_t(y) \geq 0$ decreases with income. Intuitively, higher-income consumers may have greater access to collateral and more easily verifiable repayment capacity, resulting in lower verification and enforcement costs for the financiers. The zero-profit condition for an advance A in exchange for repayment of one unit of cash at the beginning of the following year is

$$[1 + \tau_t(y_i)]A = \varrho.$$

That is, the amount consumer i can borrow today against one unit of cash received at the beginning of the following year is

$$A = \frac{\varrho}{1 + \tau_t(y_i)}.$$

Therefore, the consumer values one unit of future cash in terms of current consumption at

$$d(y_i) \equiv \frac{\varrho}{1 + \tau_t(y_i)}. \tag{12}$$

Since $\tau_t(y)$ decreases with income, $d(y)$ increases with income. Thus, richer consumers value future cash more because they face lower borrowing costs, even if their time preferences are the same as those of poorer consumers.

To obtain the functional form in Section 6, parameterize the cost as

$$\tau_t(y) = \left(\frac{e^{\kappa}}{y}\right)^{\theta}, \qquad \theta > 0, \quad \kappa \in \mathbb{R}. \tag{13}$$

Equation (9) then follows from equations (12) and (13).

C.2 Static Representation of the Dynamic Choice Problem

This appendix derives the static utility index in equation (4) and the optimal repair decision in Section 5 from a dynamic vehicle ownership problem.

Bellman equations Following Section 5, the per-period payoff for consumer i from acquiring product j and receiving one year of its services is

$$\widetilde{u}_{ijt} = X'_{jt}\beta - \alpha p_{jt} + \xi_{jt} + \epsilon_{ijt}, \qquad \widetilde{u}_{i0t} = \epsilon_{i0t}.$$

The parameter $\alpha > 0$ is the marginal utility of money.

Let $V_{it}(k, c)$ denote consumer i's expected discounted utility in year t, given an inherited vehicle of product k with repair-cost draw c and the current preference shocks. Let $V_{it}(0)$ denote the corresponding value when the consumer enters the year without a vehicle. Because retaining a repaired vehicle is equivalent to selling and repurchasing it at price p_{kt}, I use the latter representation to write the consumer's problem. The corresponding Bellman equations are

$$V_{it}(k, c) = \max_{\substack{\chi \in \{0,1\} \\ j \in \mathcal{J}_t \cup \{0\}}} \left\{ \widetilde{u}_{ijt} + \alpha\chi(p_{kt} - c) + d(y_i)\mathbb{E}_t \left[\begin{cases} V_{i,t+1}(j^+, c'), & j \neq 0 \\ V_{i,t+1}(0), & j = 0 \end{cases} \right] \right\}, \tag{14}$$

and

$$V_{it}(0) = \max_{j \in \mathcal{J}_t \cup \{0\}} \left\{ \widetilde{u}_{ijt} + d(y_i)\mathbb{E}_t \left[\begin{cases} V_{i,t+1}(j^+, c'), & j \neq 0, \\ V_{i,t+1}(0), & j = 0 \end{cases} \right] \right\}. \tag{15}$$

Here, $\chi \in \{0, 1\}$ indicates whether the inherited vehicle is repaired, $d(y_i)$ is the income-dependent discount factor, j^+ denotes product j aged by one year, $c' \sim F_{a(j^+)}$ is the repair-cost draw in the following year for $j \neq 0$, and $\mathbb{E}_t$ denotes expectations over future repair costs, preference shocks, and market prices.

The repair decision χ enters equation (14) only through $\alpha\chi(p_{kt} - c)$. It can therefore be optimized separately from the choice of j. Since $\alpha > 0$, the consumer repairs the vehicle when $c < p_{kt}$ and scraps it otherwise. Therefore,

$$V_{it}(k, c) = \alpha(p_{kt} - c)_+ + V_{it}(0), \tag{16}$$

where $(x)_+ = \max\{x, 0\}$. The inherited vehicle affects the consumer's utility but not the choice of vehicle for the current year.

Static representation Define the expected net resale value of product j as

$$R_{jt} = \mathbb{E}_t \left[(p_{j^+,t+1} - c')_+ \right], \qquad R_{0t} = 0.$$

Under the stationary expectations in Section 5, consumers expect $p_{j^+,t+1} = p_{j^+t}$, so R_{jt} equals the expected net resale value defined there, $\mathbb{E}[(p_{j^+t} - c)_+]$ with $c \sim F_{a(j^+)}$. Taking expectations of equation (16) for year $t + 1$ yields

$$\mathbb{E}_t \left[V_{i,t+1}(j^+, c') \right] = \alpha R_{jt} + \mathbb{E}_t \left[V_{i,t+1}(0) \right]. \tag{17}$$

The second term is common across current vehicle choices. Substituting equation (17) into equation (15) gives

$$V_{it}(0) = d(y_i)\mathbb{E}_t\left[V_{i,t+1}(0)\right] + \max_{j\in\mathcal{J}_t\cup\{0\}}\left\{\widetilde{u}_{ijt} + \alpha d(y_i)R_{jt}\right\}.$$

The continuation term outside the maximum is common across alternatives and therefore does not affect the current vehicle choice. The resulting choice-specific utility index is

$$\begin{aligned} u_{ijt} &= \widetilde{u}_{ijt} + \alpha d(y_i)R_{jt} \\ &= X_{jt}'\beta - \alpha\left[p_{jt} - d(y_i)R_{jt}\right] + \xi_{jt} + \epsilon_{ijt}, \end{aligned}$$

with $u_{i0t} = \epsilon_{i0t}$. This is the utility specification in equation (4), so the dynamic ownership model generates the same nested logit choice probabilities and aggregate demand as the static representation in Section 5.

C.3 Equilibrium Existence

This appendix establishes existence of the equilibrium defined in Section 5, Equations (5) and (6).

Fix a year t. Products are make–model–age combinations from a finite grid with terminal age $\bar{a} = 35$ (Section 6). Let $\mathcal{I}_t$ denote the exogenously given set of importable products defined in Section 5. Define

$$\mathcal{D}_t = \{j : K_{jt} > 0\} \setminus \mathcal{I}_t, \qquad \mathcal{J}_t = \mathcal{I}_t \cup \mathcal{D}_t.$$

Products in $\mathcal{I}_t$ may be supplied through imports, while products in $\mathcal{D}_t$ are supplied only from inherited domestic stocks. Products that are not importable and have no inherited stock are unavailable and are excluded from $\mathcal{J}_t$. The importable set is held fixed across policy scenarios, subject to the applicable age restriction, while equilibrium import flows may be zero.

Let $p_t = (p_{jt})_{j\in\mathcal{J}_t}$ denote the vector of equilibrium prices, and let $\bar{p}_{jt}$ denote the exogenous landed price for each $j \in \mathcal{I}_t$. The equilibrium conditions for importable products, including the zero-import boundary, are

$$Q_{jt}^d(p_t) = S_{jt}(p_{jt}) + N_{jt}, \qquad N_{jt} \geq 0, \qquad p_{jt} \leq \bar{p}_{jt}, \qquad N_{jt}(\bar{p}_{jt} - p_{jt}) = 0, \qquad j \in \mathcal{I}_t, \tag{18}$$

and for products supplied only from inherited domestic stocks,

$$N_{jt} = 0, \qquad Q_{jt}^d(p_t) = S_{jt}(p_{jt}), \qquad j \in \mathcal{D}_t. \tag{19}$$

Imports can cease within $\mathcal{I}_t$, with prices falling below landed prices. Prices in $\mathcal{D}_t$ clear domestic markets without a landed-price restriction. Prices outside $\mathcal{J}_t$ that enter continuation values are imputed within each policy scenario and taken as given when solving for p_t.

For $a(j) < \bar{a}$, p_{j^+t} is the equilibrium price of the successor if $j^+ \in \mathcal{J}_t$ and an imputed continuation price otherwise. Under stationary expectations,

$$\begin{aligned} R_{jt}(p_t) &= \left[1 - h_{j^+t}(p_{j^+t})\right]\left[p_{j^+t} - \bar{c}_{j^+t}(p_{j^+t})\right] \\ &= \mathbb{E}\left[(p_{j^+t} - c)_+\right], \qquad c \sim F_{a(j^+)}. \end{aligned}$$

The expectation incorporates the possibility of scrappage and implies $0 \le R_{jt} \le p_{j^+t}$. At terminal age $\bar{a}$, the successor's repair cost is infinite, so $h_{j^+t} = 1$, $R_{jt} = 0$, and price equals the user cost.

Maintain the following regularity conditions: (i) $0 < \mathcal{M}_t < \infty$ and $0 \le K_{jt} < \infty$ for all j; (ii) $X'_{jt}\beta + \xi_{jt}$ is finite for every product, $\alpha > 0$, $0 \le \sigma < 1$, and $0 \le d(y) \le \varrho < 1$; and (iii) for each age $a \le \bar{a}$, F_a is continuous with lower support bound $\ell_a \ge 0$, where ℓ_a is the minimum repair cost at age a, and satisfies $F_a(\ell_a) = 0$ and $F_a(p) \to 1$ as $p \to \infty$, while $F_a \equiv 0$ for $a > \bar{a}$.

Proposition 1 (Existence)**.** *Under the regularity conditions, an equilibrium satisfying* (18)–(19) *exists.*

Proof. Suppress t and write $G_j(p) = S_j(p_j) - Q_j^d(p)$. The result is immediate if $\mathcal{J}$ is empty. Otherwise, choose $\bar{P}$ larger than all landed prices and imputed continuation prices, and define

$$\mathcal{P} = \prod_{j \in \mathcal{I}} [0, \bar{p}_j] \times \prod_{j \in \mathcal{D}} [0, \bar{P}].$$

Under the regularity conditions, demand and supply are continuous. On the lower boundary $p_j = 0$, supply is zero because $F_{a(j)}(0) = 0$ and demand positive, so $G_j(p) < 0$. On the upper boundary $p_j = \bar{P}$, for $j \in \mathcal{D}$, the resale bound implies

$$p_j - d(y)R_j(p) \ge (1 - \varrho)\bar{P}.$$

The nested-logit formula with an outside option gives

$$s_j(y) \le \exp(\delta_j + \alpha d(y)R_j(p)) = \exp(X'_j\beta + \xi_j - \alpha[p_j - d(y)R_j(p)]).$$

Therefore

$$Q_j^d(p) \le \mathcal{M} \exp(X'_j\beta + \xi_j - \alpha(1 - \varrho)\bar{P}) \to 0 \text{ and } S_j(\bar{P}) = F_{a(j)}(\bar{P})K_j \to K_j > 0 \text{ as } \bar{P} \to \infty.$$

Because this upper bound on demand does not depend on the other product prices or on income, we can choose $\bar{P}$ large enough that supply exceeds demand for every $j \in \mathcal{D}$ whenever $p_j = \bar{P}$. Equivalently, $G_j(p) > 0$ on every domestic upper boundary.

For $\eta > 0$, Brouwer's theorem gives a fixed point p^* of the continuous map $\mathcal{T}(p) = \Pi_{\mathcal{P}}[p - \eta G(p)]$, where $\Pi_{\mathcal{P}}$ projects each p_j onto its admissible interval in $\mathcal{P}$. For every j, the sign of G_j at the lower bound rules out $p_j^* = 0$. For $j \in \mathcal{D}$, the sign at the upper bound also rules out $p_j^* = \bar{P}$, so p_j^* is interior and therefore $G_j(p^*) = 0$. On $\mathcal{I}$, either $p_j^* < \bar{p}_j$ and $G_j(p^*) = 0$, or $p_j^* = \bar{p}_j$ and $G_j(p^*) \le 0$. Setting $N_j^* = -G_j(p^*)$ on $\mathcal{I}$ and zero on $\mathcal{D}$ yields (18)–(19).

□

D Estimation Details

D.1 Identification of Scrappage Parameters

This appendix illustrates the identification of scrappage parameters through a simple example.

Suppose that there are only 3 periods, $t = 1, 2, 3$. In addition, suppose that there are four mutually exclusive, but not necessarily collectively exhaustive, groups of products, $g = 1, 2, 3, 4$, with (1) a common age within each group in each period, (2) different ages across groups, and (3) observed shares at the beginning of the third period. Group 1 consists of products newly introduced in period 2 that have not yet faced scrappage, while each of the other groups has faced one scrappage draw at different ages in period 2. Let $N_{gt} \geq 0$ denote the number of first-time registrations of group g in period t, with $N_{g1} > 0$ for $g = 2, 3, 4$ and $N_{12} > 0$, and let π_g^{obs} denote the observed share of group g. Because group 1 has experienced no scrappage, the survival probabilities of the other groups satisfy

$$1 - h_g = \frac{N_{12}\pi_g^{obs} - N_{g2}\pi_1^{obs}}{N_{g1}\pi_1^{obs}}, \qquad g = 2, 3, 4.$$

Thus, known numbers of initial registrations and observed age shares reveal these survival probabilities without requiring information on total fleet size.

Suppose groups 2 and 3 faced scrappage at prices equal to their respective age-specific medians. Their scrappage probabilities are

$$h_g = \bar{h}(a_g) = \Lambda\left(\vartheta_0 + \vartheta_1 a_g/10\right), \qquad g = 2, 3.$$

The two recovered scrappage probabilities at different ages pin down the overall level of scrappage, ϑ_0, and its age gradient, ϑ_1.

Suppose products in group 4 faced scrappage in period 2 at age a_4 and a common price p_4 different from the corresponding age-specific median across periods 1 and 2:

$$h_4 = \bar{h}(a_4)\left(\frac{p_4}{\tilde{p}_{a_4}}\right)^{\gamma}.$$

Conditional on ϑ_0 and ϑ_1, the recovered scrappage probability for this group identifies γ through its price relative to the age-specific median.

More generally, products in each group can face multiple scrappage draws, and the data reveal cumulative rather than one-period survival. Suppose groups 1, 2, and 3 face scrappage at their respective age-specific median prices in every period. The stock of group g at the beginning of period T is

$$K_{gT} = \sum_{\tau<T} N_{g\tau} \prod_{s=\tau+1}^{T-1} \left(1 - h_{gs}\right).$$

One sufficient condition for local identification is

$$\operatorname{rank}\left[\frac{\partial}{\partial(\vartheta_0, \vartheta_1)}\begin{pmatrix} K_{2T}/K_{1T} \\ K_{3T}/K_{1T} \end{pmatrix}\right] = 2$$

under the true parameters. Intuitively, this requires that the historical registration histories of products at different terminal ages must imply sufficiently different numbers and ages of scrappage

draws for changes in ϑ_0 and ϑ_1 to have distinguishable effects on the predicted terminal age distribution.

Finally, suppose products in group 4 face prices p_{4t} that differ from their age-specific medians. Their scrappage probabilities are

$$h_{4t} = \bar{h}(a_{4t}) \left(\frac{p_{4t}}{\tilde{p}_{a_{4t}}} \right)^{\gamma}.$$

Conditional on ϑ_0 and ϑ_1, the observed share of group 4 imposes

$$K_{4T}(\vartheta_0, \vartheta_1, \gamma) = \frac{\pi_4^{obs}}{\pi_1^{obs}} K_{1T}(\vartheta_0, \vartheta_1).$$

One sufficient condition for local identification of γ is

$$\frac{\partial K_{4T}(\vartheta_0, \vartheta_1, \gamma)}{\partial \gamma} \neq 0$$

under the true parameters. Price ratios above and below one impose opposing effects of γ on scrappage probabilities. The condition requires that these effects do not exactly offset in the stock in period T.

D.2 Formulas

Expected repair cost conditional on survival Under the assumption that the repair cost follows an age-specific Pareto distribution, the expected repair cost conditional on survival, $\bar{c}_{jt}$, has a closed-form expression:

$$\bar{c}_{jt} = \frac{\gamma}{\gamma + 1} \frac{b(a(j))^{-1/\gamma} - b(a(j)) p_{jt}^{\gamma+1}}{1 - b(a(j)) p_{jt}^{\gamma}}, \qquad \gamma \neq -1.$$

Moments on the age distribution With the stock inherited at the beginning of 2024, $K_{j,2024}$ as in equation (8), and first-time registrations in the first two quarters of 2024, I compute the model-implied stock of each product in July 2024 as

$$\begin{aligned} K_{j,2024}^{\text{July}} = K_{j,2024}(1 - h_{j,2024}^{q_1})^{1/4}(1 - h_{j,2024}^{q_2})^{1/4} \\ + N_{j,2024}^{q_1}(1 - h_{j,2024}^{q_2})^{1/4} + N_{j,2024}^{q_2}, \end{aligned}$$

where $h_{j,2024}^{q}$ is the annual scrappage probability of product j evaluated at its price in quarter q of 2024, and $N_{j,2024}^{q}$ is the number of first-time registrations of product j in that quarter. For age group g with ages $\mathcal{A}_g$, the model-implied share is then

$$\hat{\pi}_g = \frac{\sum_{j:\, a(j) \in \mathcal{A}_g} K_{j,2024}^{\text{July}}}{\sum_j K_{j,2024}^{\text{July}}},$$

and π_g^{obs} is the share of sampled vehicles with ages in $\mathcal{A}_g$. Because the shares sum to one, I omit one of the seven age groups and construct $g_A = \hat{\pi} - \pi^{obs}$, where $\hat{\pi}$ and π^{obs} are vectors of model-implied and observed shares for the six remaining groups.

Moments on income sorting The model-implied mean log annual income of registrants of product j in year t is

$$\hat{\mu}_{jt} = \frac{\int \ln y \, s_{jt}(y) \, dF_t(y)}{s_{jt}}.$$

For each age a, I compute the model-implied mean log annual income as

$$\hat{\mu}_a = \frac{\sum_t \sum_{j:\, a(j)=a} n_{jt} \hat{\mu}_{jt}}{\sum_t \sum_{j:\, a(j)=a} n_{jt}},$$

where n_{jt} is the number of first-time registrants of product j in year t with matched income. I match these model-implied age-specific means to the corresponding observed means among income-matched first-time registrants.

In addition, I match the model-implied and observed mean log annual incomes across price terciles within each age bin, after demeaning the tercile-specific means within that bin. For each price tercile k within age bin b, the model-implied and observed mean log annual incomes are

$$\hat{\mu}_{bk} = \frac{\sum_{(j,t) \in C_{bk}} n_{jt} \hat{\mu}_{jt}}{\sum_{(j,t) \in C_{bk}} n_{jt}}, \qquad \mu_{bk}^{obs} = \frac{\sum_{(j,t) \in C_{bk}} n_{jt} \mu_{jt}^{obs}}{\sum_{(j,t) \in C_{bk}} n_{jt}},$$

where C_{bk} is the set of product-year observations in age bin b whose prices fall in tercile k within their respective years, and μ_{jt}^{obs} is the mean log annual income of income-matched registrants of product j in year t. I then demean the mean log annual incomes across price terciles within each age bin. The resulting moment for tercile k of age bin b is

$$\left(\hat{\mu}_{bk} - \sum_{k'} \omega_{bk'} \hat{\mu}_{bk'} \right) - \left(\mu_{bk}^{obs} - \sum_{k'} \omega_{bk'} \mu_{bk'}^{obs} \right),$$

where ω_{bk} is the share of income-matched registrants in age bin b whose product-years fall in price tercile k.

Own-user-cost elasticities Write the income-specific user cost as

$$r_{jt}(y) = p_{jt} - d(y) R_{jt},$$

and write

$$s_{jt}(y) = s_{j|m,t}(y) s_{m,t}(y).$$

For a consumer with income y, the own-user-cost elasticity is

$$\varepsilon^r_{jj,t}(y) = -\alpha r_{jt}(y)\left[\frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma}s_{j|m,t}(y) - s_{jt}(y)\right].$$

Integrating over the income distribution,

$$\varepsilon^r_{jj,t} = \frac{\int s_{jt}(y)\varepsilon^r_{jj,t}(y)\,dF_t(y)}{s_{jt}}, \qquad s_{jt} = \int s_{jt}(y)\,dF_t(y),$$

where $F_t(y)$ is the income distribution in market t.

Diversion ratios Consider a marginal increase in the user cost of product j. For another product $k \neq j$ of the same make,

$$\frac{\partial s_{kt}(y)}{\partial r_{jt}(y)} = \alpha s_{kt}(y)\left[\frac{\sigma}{1-\sigma}s_{j|m,t}(y) + s_{jt}(y)\right], \qquad m(k) = m(j).$$

The share of demand displaced from j that is diverted to other products of the same make is therefore

$$D^{\text{same}}_{jt} = \frac{\int \sum_{\substack{k\neq j \\ m(k)=m(j)}} \frac{\partial s_{kt}(y)}{\partial r_{jt}(y)}\,dF_t(y)}{-\int \frac{\partial s_{jt}(y)}{\partial r_{jt}(y)}\,dF_t(y)}.$$

D.3 Linear structural parameter estimates

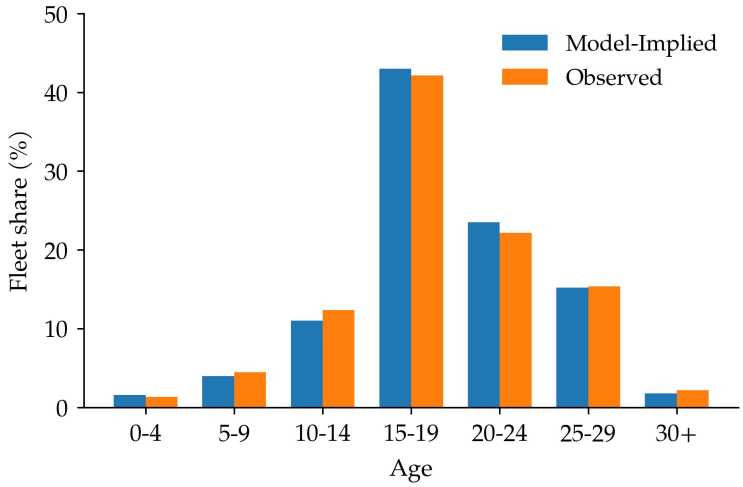
Table A4 reports the linear structural parameter estimates, $\hat{\beta}$, under the nonlinear structural parameter estimates in Table 5.

Age/10	0.073
	(0.195)
$(\text{Age}/10)^2$	-0.185^{***}
	(0.063)
Engine size (1,000 cc)	0.458^{***}
	(0.092)
Weight (1,000 kg)	1.076^{***}
	(0.168)
Constant	-9.639^{***}
	(0.238)
Make FE	✓
Year FE	✓
Observations	3,207
R^2	0.753

Notes: This table reports estimates of the linear parameters from Equation (10), conditional on the nonlinear parameter estimates reported in Table 5. Standard errors are computed using the GMM sandwich estimator, clustered at the make × Japanese fiscal year level, treating the nonlinear parameters as known. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

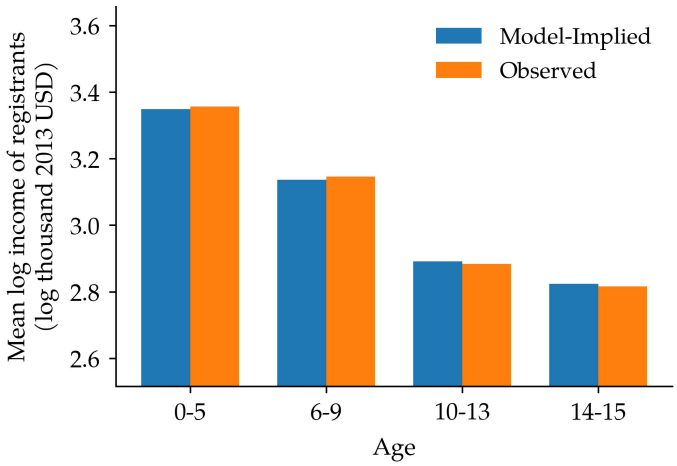
Table A4: Linear structural parameter estimates

D.4 Model Fit



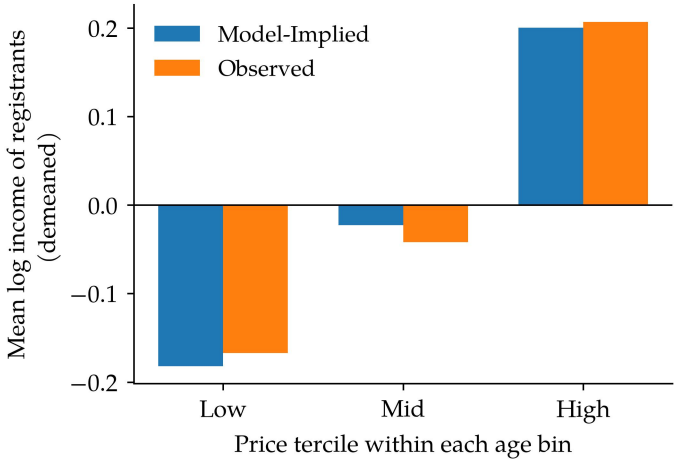
Notes: The figure compares the observed age distribution of the fleet in July 2024 with the model-implied distribution, using the same age groups as in the data on the age distribution from Crowe et al. (2025).

Figure A12: Observed vs. model-implied age distributions



Notes: The figure plots the model-implied and observed mean log income of registrants matched with annual incomes.

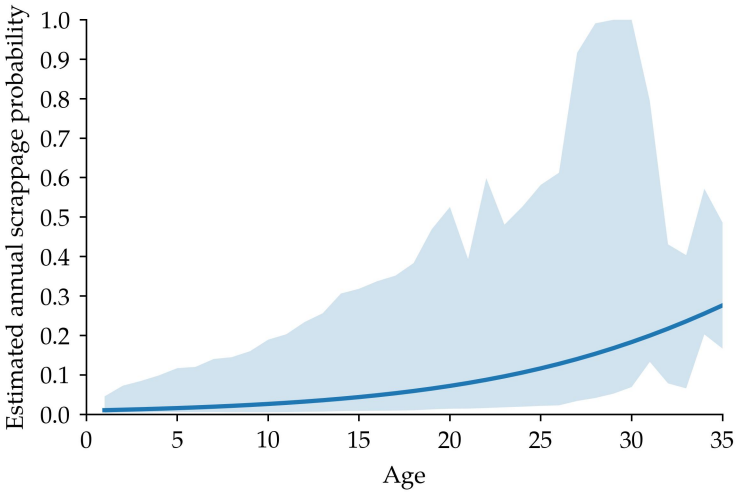
Figure A13: Observed vs. model-implied mean log income of registrants across age bins



Notes: The figure compares the observed and model-implied mean log annual income of registrants across price terciles within age bins (0–5, 6–9, 10–13, and 14–15 years), demeaned across price terciles within each age bin.

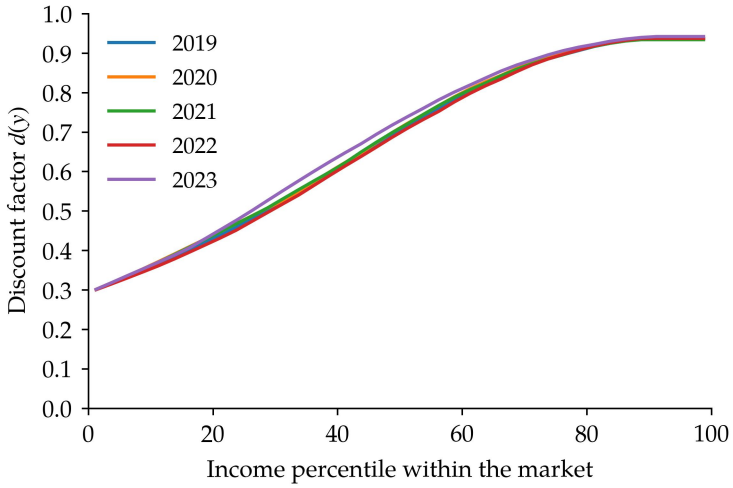
Figure A14: Observed vs. model-implied mean log income of registrants across price terciles

D.5 Implications



Notes: The figure plots the annual scrappage probability for each age between 1 and 35 estimated from Section 6, evaluated at the age-specific median price. The shaded area shows the range of the scrappage probabilities across all products and years between 2019 and 2023.

Figure A15: Estimated annual scrappage probability over age



Notes: The figure plots the discount factor $d(y)$ in Equation (9) at the estimates in Table 5 against the percentile of income among individuals in each market between 2019 and 2023. $\varrho = 0.95$ is the upper bound of $d(y)$.

Figure A16: Distributions of the discount factor

D.6 Robustness

Table A5 reports the nonlinear structural parameter estimates when the stock at the start of 2019 is reconstructed from first-time registrations between 2005 and 2018 instead of between 2000 and 2018. The main conclusions remain unchanged under these estimates. For example, the estimated effects of Japanese subsidies in Section 7.2 are similar in both levels and percentage changes. Over 2019–2028, the subsidies increase NO_x emissions by 257.0 metric tons (1.97%) and PN emissions by 12.0×10^{21} particles (2.28%), compared with 263.8 metric tons (2.07%) and 12.2×10^{21} particles (2.35%) in Table 7. The subsidies also increase consumer surplus by 185.71 million USD (2.29%),

compared with 187.91 million USD (2.33%) in Table 7.

Parameter	Estimate	S.E.
Panel A. Utility		
Price coefficient (α)	0.322^{***}	(0.072)
Discount factor: constant (κ)	2.014^{***}	(0.153)
Discount factor: log income coefficient (θ)	3.008^{***}	(0.498)
Nesting parameter (σ)	0.736^{***}	(0.082)
Panel B. Scrappage hazard		
Constant (ϑ_0)	-4.840^{***}	(0.319)
Age coefficient (ϑ_1)	1.071^{***}	(0.165)
Price elasticity (γ)	-0.913^{***}	(0.267)

Notes: The estimator and sample are those of Table 5, except that the stock at the start of 2019 is reconstructed from first-time registrations between 2005 and 2018 instead of between 2000 and 2018. GMM sandwich standard errors are in parentheses. Prices and incomes are in thousands of 2013 USD. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A5: Nonlinear structural parameter estimates with the 2019 stock reconstructed from first-time registrations since 2005