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Global Policy Spillovers: How Environmental Policies Propagate through Product Attributes

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Abstract

How should policymakers evaluate policy impacts when firms design products for global markets? Standard economic analyses typically focus on domestic outcomes, implicitly assuming that policies affect only the jurisdiction in which they are enacted. Yet multinational firms often harmonize product design across markets, creating the potential for policies implemented in one country to generate global spillovers through changes in product attributes. We call this phenomenon "attribute propagation" and develop a framework to measure and assess its quantitative importance. Applying this framework to an environmental policy affecting automobiles, we find that a fuel-economy subsidy in Japan led to significant improvements in the fuel economy of vehicles sold in the United States. We then develop a model of multinational automobile markets featuring cross-market cost complementarity as a key mechanism driving attribute propagation. Using the estimated model, we conduct counterfactual simulations to quantify environmental benefits accounting for the policy's global spillover effects. We find that global spillover effects are first-order—a majority of the CO_2 emissions reductions induced by the Japanese policy arise through its impact on the U.S. automobile market. These findings

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suggest that standard economic analyses that abstract from attribute propagation can substantially understate the full policy impact. More broadly, attribute propagation provides a new lens for evaluating environmental, safety, antitrust, and technology policies in a global economy.

1 Introduction

How should we evaluate policies enacted in one jurisdiction that affect products sold worldwide? Standard economic analysis typically focuses on domestic outcomes when assessing impacts of a domestic policy. However, in a world where multinational firms design products for global markets, policies implemented in one country can propagate internationally by inducing changes in product attributes. This mechanism, which we call attribute propagation, represents a potentially significant yet understudied channel through which domestic policies generate global effects through a form of cross-market cost complementarity. Accounting for attribute propagation can fundamentally reshape policy evaluation, as conventional economic analyses that abstract from this channel may significantly understate the overall effects of policies in areas including environmental regulations, safety standards, or antitrust remedies.

In this paper, we develop a framework to measure attribute propagation and assess its significance for policy evaluation. Our empirical application is an environmental policy for automobiles, a setting in which attribute propagation may be particularly important because automobiles are designed and marketed by multinational firms. When automakers change a vehicle's attribute in response to a policy in one market, this may lower the cost of corresponding changes to the twin vehicle sold in other markets. We show that an environmental subsidy enacted in Japan generated substantial environmental benefits in the United States through attribute propagation. We then quantify the magnitude by which standard economic analyses understate the policy's overall impact when they abstract from this global spillover effect. Our estimates suggest that the impacts of attribute propagation are first-order in our context: the majority of the greenhouse gas emissions reductions induced by the subsidy in Japan occurs in the United States.

Environmental policy in the automobile sector provides a natural setting to study this phenomenon, but attribute propagation can arise in many other contexts, triggered by safety regulations, antitrust rules, or differences in consumer preferences. For example, the European Union's 2022 directive requiring USB-C charging ports led Apple to adopt USB-C globally in subsequent iPhone models, rather than maintaining separate Lightning and USB-C versions. Similarly, pharmaceutical firms often comply worldwide with the stringent guidelines of the International Council for Harmonisation in order to access major markets, even when operating in countries with less demanding regulatory standards. In aviation, manufacturers such as Boeing and Airbus design aircrafts to satisfy both Federal Aviation Administration and European Union Aviation Safety Agency requirements simultaneously and then market these designs globally. Likewise, the European Union's Registration, Evaluation, Authorisation and Restriction of Chemicals (REACH) regulation has become a de facto global standard, with firms adopting E.U. chemical requirements across their product lines to maintain access to the European market.

Each of these examples illustrates how policies in one jurisdiction can propagate through firms' global product-design decisions, generating spillovers that extend well beyond the regulating authority's borders. Despite its potentially ubiquitous nature, the empirical magnitude and policy significance of attribute propagation remain largely unexplored prior to our study.

Our analysis begins with a difference-in-differences (DID) design that exploits variation generated by a Japanese fuel-economy subsidy introduced in 2009. The policy created strong incentives for firms to improve the fuel economy of models sold in Japan. We leverage the fact that while many models sold in Japan are also marketed abroad (e.g., in both Japan and the United States), multinational Japanese automakers also produce vehicles for foreign markets that are not sold in Japan. This feature allows us to construct treatment and control groups within the U.S. automobile market, where the former can be affected by the Japanese subsidy through attribute propagation. We show that the treatment and control groups exhibit parallel pre-trends in fuel economy before the policy's introduction, and that our results are robust to the inclusion of a variety of control variables.

The DID analysis provides statistical evidence that the Japanese fuel-economy subsidy propagated to the U.S. market. Specifically, the subsidy in Japan led to an 8.65% improvement in the fuel economy of affected vehicles sold in the United States. We estimate that the direct effect of the subsidy in Japan was a 25.2% improvement in fuel economy. Taken together, these results imply a substantial but incomplete "pass-through" of fuel-economy gains from Japan to the U.S. market.

Importantly, these estimates do not imply that the policy's environmental impact in the United States is 0.34 (= 8.65 / 25.2) of its impact in Japan. This is because environmental externalities depend not only on fuel-economy improvements but also on sales volumes and vehicle miles traveled, which is much higher in the U.S. To evaluate this question, we introduce a statistic, the spillover multiplier of environmental impacts, which is the ratio of the Japanese policy's effect on CO_2

reductions in the United States and Japan over its domestic effect. We find that the DID results indicate that the spillover multiplier equals 5.42. This implies that the total CO_2 reduction is 5.42 times larger than the Japanese domestic CO_2 reduction.

A limitation of the DID design is that it does not capture potential indirect equilibrium effects: vehicles in the US that are not affected directly by the policy may adjust their fuel economy in response to changes in the fuel economy of competing vehicles. To account for these equilibrium effects, the second part of our paper develops a structural model of multinational vehicle markets with global spillovers. The model features two markets served by a mix of multinational products and products sold in a single location, in which firms choose vehicle fuel economy and prices under Nash–Bertrand competition.

Our model links the two markets through firms' cost functions. In particular, the cost function includes a fixed cost of improving fuel economy. We allow for cross-market complementarities by incorporating potential economies of scope between a vehicle model's fuel economy improvements in Japan and those of its corresponding model in the United States—improving fuel economy in Japan for a given model could lower the redesign cost of improving fuel economy for the same model in the U.S and vice versa.

We estimate the model following the tradition of Berry, Levinsohn, and Pakes (1995) and the approach of Fan (2013) and Barwick, Kwon, and Li (2024a) for identifying the slope of the fixed cost of adjusting product attributes. We estimate the automobile demand system separately for Japan and the United States to allow for differences in consumer preferences across the two markets. We then recover marginal costs and the slope of fixed costs using the first-order conditions implied by automakers' profit maximization. We find statistical evidence of economies of scope in fuel economy across markets for a given vehicle model. This economy of scope is the basis of attribute propagation in the model.

Finally, we use the model and estimated parameters to conduct a counterfactual simulation in which we remove the fuel-economy subsidy policy and compute a new equilibrium. With the indirect equilibrium effect, the spillover multiplier becomes 4.04, which implies that the total CO_2 reduction is 4.04 times larger than the Japanese domestic CO_2 reduction. This finding suggests that while accounting for indirect equilibrium effects is important, it does not substantially change our conclusions—while the Japanese subsidy policy reduces CO_2 emissions in both Japan and the United States, the resulting reductions in the United States are substantially larger than the domestic reductions in Japan. Abstracting from the global spillover effect, in this case, would considerably understate policy impacts.

Related Literature and Our Contributions—To our knowledge, our paper is the first to formally introduce the concept of attribute propagation into the economics literature, and to quantify its causal effects and magnitude for policy evaluation. Related ideas have been discussed in influential work in political science and law—most notably in studies of the "California effect" (Vogel, 1995) and the "Brussels effect" (Bradford, 2020). This literature theorizes that firms may find it cost-effective to design products that comply with the most stringent standards they face and then sell those products globally, rather than maintain separate production lines for different markets. However, we are unaware of any prior study that develops a formal economic framework to quantify this mechanism or to evaluate its magnitude in shaping policy impacts.

Our study is related to the environmental economics literature that examines other mechanisms through which policies in one jurisdiction generate effects beyond their borders. A prominent example is the pollution haven hypothesis, which posits that tightening environmental regulation in one location can lead firms to shift production locations to other markets (Levinson and Taylor, 2008; Copeland, 2008), or to export pollution-intensive used products to other countries (Davis and Kahn, 2010; Tanaka, Teshima, and Verhoogen, 2022). While closely related, our focus is distinct from this literature, which typically assumes that product design remains unaffected by a country's regulation. In contrast, we study attribute propagation—a channel through which regulatory standards in one market reshape product attributes globally.

Another example is cross-country technology spillovers through innovation or learning by doing. If local policy accelerates innovation or learning by doing, it can reduce technology costs at the industry level and thereby affect other markets. This mechanism has been documented for electric vehicle batteries (Barwick, Kwon, Li, and Zahur, 2024b; Head, Mayer, Melitz, and Yang, 2025), vehicle emission technologies (Gessner, 2025), and solar panels (Gerarden, 2023; Banares-Sanchez, Burgess, László, Simpson, Van Reenen, and Wang, 2026). Although this mechanism is important, it is difficult to explain our empirical findings through this channel for two reasons. First, if the spillover operated through this mechanism, our difference-in-differences estimates would likely show little effect because our empirical design compares vehicles sold by the same firm in the same market.

Second, we find that the cross-market cost complementarity is primarily driven by vehicles produced in the same location and shipped to different markets. We therefore interpret our form of attribute propagation—arising from economies of scope as a form of cross-market cost complementarity—as distinct from the prior literature, which focuses on learning by doing and innovation.

Our paper also contributes to a large literature on environmental policies in automobile markets. A number of papers examine fuel economy regulations, including their effects on vehicle markets and welfare (Goldberg, 1998; Anderson and Sallee, 2011; Jacobsen, 2013; Ito and Sallee, 2018), the role of technology adoption and attribute trade-offs in regulatory compliance (Knittel, 2011; Klier and Linn, 2016; Reynaert, 2021), and the interactions between nested state and federal regulations (Goulder, Jacobsen, and van Benthem, 2012). A related literature evaluates subsidies and feebates for clean vehicles, including hybrid vehicle tax credits (Beresteanu and Li, 2011), electric vehicle subsidies (Muehlegger and Rapson, 2022; Xing, Leard, and Li, 2021; Langer and Lemoine, 2022; Allcott, Reigner, Maydanchik, Shapiro, and Tintelnot, 2026), and the French bonus–malus system (D'Haultfœuille, Givord, and Boutin, 2014; Durrmeyer and Samano, 2018; Durrmeyer, 2022). Other work studies how gasoline prices and consumers' valuation of fuel costs shape vehicle demand and equilibrium outcomes (Busse, Knittel, and Zettelmeyer, 2013; Levinson, 2019; Levinson and Sager, 2023; Gillingham, Houde, and van Benthem, 2021), as well as how used-vehicle markets and scrappage decisions mediate the effects of new-vehicle policies (Jacobsen and van Benthem, 2015; Jacobsen, Sallee, Shapiro, and van Benthem, 2023). While this literature has substantially advanced our understanding of environmental policy for automobiles, none of those papers incorporate attribute propagation into their empirical or theoretical frameworks. Our findings suggest that the benefits (or costs) of environmental policies estimated in the existing literature may be substantially understated when this channel is ignored.

Outside environmental economics, several recent papers examine important questions for the global automobile industry. For example, Castro-Vincenzi (2024) studies how floods disrupt plant-level production and induce firms to reallocate output to unaffected facilities. Closely related to our study are Castro-Vincenzi, Menaguale, Morales, and Sabal (2024) and Sabal (2024), which investigate how consumer preferences, supply costs, or regulatory differences influence product entry decisions across markets. Our study differs from this literature in two respects. First, our focus is on attribute propagation rather than production reallocation or product entry. Environmental policies typically target specific product attributes (e.g., fuel economy or emissions rates), and automakers are known to respond by adjusting those attributes (Ito and Sallee, 2018; Kellogg, 2020; Barwick, Kwon, and Li, 2024a). In fact, we empirically find that the policy we examine significantly affected the targeted attribute but had little impact on product entry or exit. This evidence suggests that attribute propagation is likely to be the primary adjustment margin in our context, even though production reallocation or product entry can be important channels in other settings. A second distinction is that we focus on the implications of attribute propagation for environmental impacts. We introduce a policy-relevant parameter—the spillover multiplier of environmental impacts—which quantifies how much a regulation's environmental impact is amplified through cross-market attribute adjustments. This framework enables us to assess the quantitative importance of attribute propagation for policy evaluation, which is particularly important for global environmental problems but also applicable to evaluating global policy spillovers in other policy domains.

2 Background and Data

2.1 Japanese government's subsidy for fuel-efficient cars

Starting in 2009, the Japanese government provided a subsidy for consumers purchasing a new car with fuel economy in excess of the fuel economy target. There are three unique features of this policy that will help our empirical analysis. First, the subsidy ranged approximately between $700 and $1,500, which was a significant amount for consumers (about 5 to 10% of an average new car price).

Second, this subsidy was based on each vehicle's own fuel economy, rather than a corporate average fuel economy. A model was qualified for the subsidy if the model's fuel economy was above the fuel economy target given the model's weight. This allows us to exploit variation at the model level rather than at the corporate level.

Third, because the fuel economy target was designed as a step function of weight, the policy created variation across models in the difficulty of meeting the fuel economy target. For example, if a model's combination of fuel economy and weight before the policy was enacted (i.e., the pre-policy period) was already close to the target, the model would be able to qualify for the subsidy with small changes in its product attributes. In contrast, if a model was located far from the target function, it would need relatively larger changes in its product attributes in order to qualify for the consumer subsidy.

Fourth, many models sold in the U.S. market were also possibly affected by Japan's policy because they were sold in both countries, whereas there were many other models in the U.S. market that were not sold in Japan. This provides another source of variation to conduct difference-in-differences (DID) estimation. We take advantage of these four features to analyze data with three empirical methods.

2.2 Potential global spillover effects

Our question is whether Japan's fuel-economy subsidy policy generated global spillover effects through products sold by multinational firms. Before we begin with empirical analysis, it is helpful to see key descriptive statistics in the Japanese and global car markets to hypothesize which automakers are more likely to create such spillovers.

Figure 1 shows the market shares for new car sales in the Japanese car market in 2012 (Panel A). The top 10 were all Japanese automakers, and about 80% of new car sales were from Japanese firms. In contrast, while American firms sold a variety of cars in Japan, their sales quantities were extremely small; they are part of "other" firms in the figure. These statistics imply that qualifying for the fuel-economy subsidy was likely to be important for Japanese firms but not for American firms—it is unlikely to make sense for American firms to incur fixed costs to change their car designs to qualify for the subsidy as their sales quantities were low.

Panel B of Figure 1 illustrates the extent to which the Japanese market is important for each automaker relative to their worldwide sales. This figure shows again that Japan is a key market for Japanese firms but not for American firms. In addition, this figure suggests that for most of the major Japanese firms, such as Toyota, Honda, Nissan, Suzuki, Subaru, and Mitsubishi, Japan is a major market but Japan's share relative to these firms' worldwide sales are around 15-20%. These firms have high sales quantities in the rest of the world.

Overall, these descriptive statistics suggest that the global spillover effects can be heterogeneous among automakers, depending on their market share in Japan and the rest of the world. We provide our empirical analysis in Section 3.1 to test this hypothesis.

2.3 Data

We use three primary datasets. The first dataset records car specifications data from Japan and the United States. The Japanese and U.S. data sources for the specifications datasets are Car Sensor and Wards Auto data, respectively. The second dataset is monthly car sales quantity data at the model level from Marklines. The third dataset consists of model-level monthly automobile production data from MarkLines, which report production quantities and production locations. Our datasets covers all car models sold in Japan and the United States between the 2003 and 2019 model years.

3 Difference-in-Differences Analysis

In this section, we use a difference-in-differences (DID) analysis to investigate whether the fuel-economy subsidy in Japan described in Section 2.1 generated global spillover effects through international car markets. Our main focus is on the US car market, although we find similar results in other countries, which we show in the Appendix.[1]

3.1 Global Spillover Effects on Fuel Economy

During our sample period from 2003 to 2019, we observe that many vehicle models sold in the U.S. market by Japanese automakers were also offered in Japan, while many others were not. We exploit this variation to construct treatment and control groups for evaluating the impact of the Japanese subsidy, which was introduced in the 2010 model year. Using model year 2009 as the pre-policy baseline, we define the treated group as consisting of models sold in both the U.S. and Japan, and the control group as models sold in the U.S. but not in Japan.

Table A.1 reports summary statistics of vehicle characteristics in 2008—one year prior to the introduction of the Japanese fuel economy subsidy—for Japanese vehicles sold in the U.S. market. Simple differences between the treated and control groups suggest that, prior to the policy, treated vehicles had lower fuel economy, higher horsepower, and lighter weight on average. However, we find that most of these differences reflect variation across body types, which categorize vehicles into

[1] Table A.6 reports the DID results for Germany and India, which are similar to the findings for the United States presented in this section.

distinct segments.[2] In our data, both treated and control vehicles are present within each body type, allowing us to include body-type fixed effects to assess whether baseline differences persist within segments. The last column reports differences in means controlling for body-type fixed effects. Once these fixed effects are included, the baseline differences become small and statistically insignificant. Although the identification assumption of the DID design does not require balance in baseline characteristics, one of our specifications below includes interactions between time fixed effects and body types to further assess the robustness of our results.[3]

Our hypothesis is that, if the Japanese subsidy policy generated an international spillover effect on fuel economy, we would expect to observe an improvement in fuel economy for the treated group relative to the control group in the U.S. market. Our DID design is likely to yield a lower bound of the international spillover effect if there was also a within-firm technological spillover—where innovations adopted for models affected by the subsidy may be shared across untreated models within the same firm. If this was the case, it could lead to improvements in fuel economy even among the control group. Such within-firm spillovers would attenuate the estimated difference between the treated and control groups, thus making our estimates a lower bound of the international spillover effect.

Figure 2 presents the time trends of sales-weighted average log fuel economy in the U.S. market for vehicles sold by Japanese automakers. The figure indicates that the treated models—defined as those sold in both the U.S. and Japanese markets—and the control models—those sold in the U.S. but not in Japan—exhibited similar trends during the pre-policy period, spanning from 2003 to 2009. These parallel pre-trends include a decline in average fuel economy in 2008, which reflects a market-wide phenomenon driven by falling gasoline prices during that year.[4] The unweighted trends are very similar.

Following the introduction of the subsidy policy in 2009, fuel economy began to diverge between the treated and control groups, with the treated group exhibiting an increase of approximately 0.1

[2]Our dataset includes industry-standard body-type classifications: sedan, hatchback, wagon, coupe, convertible, SUV, crossover, pickup truck, and van.

[3]We take two steps to identify vehicle models that were sold in both countries. The most straightforward case is when the same model name from the same automaker is sold in both countries. A less obvious case arises when different model names are used for the same vehicle in different countries. We use each automaker's catalog information to identify models that are sold under different names across markets and match these models accordingly.

[4]It is well established that lower gasoline prices tend to reduce average fuel economy, as consumers typically respond to contemporaneous fuel prices when making vehicle purchase decisions.

log points (roughly 10%) relative to the control group. The figure further suggests that the improvement in fuel economy for the treated group did not occur entirely in the immediate aftermath of the policy's implementation. Rather, the response appears to involve both short-run and medium-to long-run adjustments. This pattern is consistent with the typical product development cycle in the automobile industry, where major specification changes to a vehicle model occur only every few years. As such, some of the automakers' responses to the subsidy policy likely materialized with a delay.[5]

While the graphical analysis provides a visual representation of the raw data trends, it does not account for potential confounding factors. To obtain DID estimates with controls, we estimate the following equation using ordinary least squares (OLS). The dataset comprises all vehicles sold by Japanese automakers in the U.S. market from 2003 to 2019, at the model-year (t) and model-by-trim (j) level:

$$\ln e_{jt} = \alpha D_{jt} + \theta_j + \lambda_t + X_{jt}\delta + \epsilon_{jt}, \tag{1}$$

where e_{jt} denotes the fuel economy, measured in miles per gallon (MPG), for vehicle trim i in model-year t. The treatment indicator D_{jt} equals 1 if the model is also sold in Japan and the model-year t is after the introduction of the Japanese subsidy. The specification includes model fixed effects (θ_j) to control for time-invariant heterogeneity across vehicle models and year fixed effects (λ_t) to account for common shocks over time. In some specifications, we additionally include a vector of control variables (X_{jt}), such as year fixed effects interacted with a truck–car indicator and year fixed effects interacted with firm indicators, to assess robustness. Standard errors are clustered at the model level to address serial correlation.

Table 1 reports the OLS estimates of Equation (1) for Japanese vehicles sold in the U.S. market. The difference-in-differences estimates in column 1 indicate that the Japanese subsidy policy generated an international spillover effect on fuel economy in the U.S. market, increasing fuel economy by 0.073 log points (7.57 percent).

In Table A.2, we replicate the same DID estimation for American automaker's vehicles in the

[5]The fuel-economy subsidy in Japan was introduced in 2009 and continued until early 2013. It was subsequently converted into a form of tax exemption, which remained in place through the end of our sample period. Thus, the policy itself was persistent.

U.S. market. As discussed in Section 2.2, although American automakers do sell a range of models in both Japan and the U.S., their sales volumes in the Japanese market are very low. Consequently, we hypothesize that American automakers have limited incentive to respond to the Japanese subsidy. The empirical results in Table A.2 support this prediction: we find economically and statistically insignificant effects on fuel economy for vehicles produced by American automakers.

3.2 Potential Threats to Identification and Robustness Analysis

The identification assumption underlying the DID estimation is the parallel trends assumption—namely, that in the absence of the Japanese subsidy policy, trends in fuel economy would have evolved similarly for the treated and control groups. A potential threat to this assumption is the presence of a confounding factor in the U.S. market that varies over time and differentially affects the treated and control groups.

Several things happened in the US auto market around this time. The Cash for Clunkers program was initiated as a stimulus program. Transactions were eligible for this subsidy only if they met minimum fuel economy requirements. This might have created an incentive to improve fuel economy. However, this would have affected both our treatment and control group, and the program was so short-lived (two months) that automakers had limited ability to respond by modifying and certifying a new configuration.

U.S. fuel-economy standards (Corporate Average Fuel Economy, or CAFE) also changed in this time period—a new law was passed in 2009 that took effect in 2012. Under CAFE, every automaker must meet a minimum sales-weighted fuel economy for their passenger car fleet and their truck fleet. As we discuss further in Section 4.2, CAFE was not a binding constraint on Japanese firms in this time period. Thus, we think CAFE is unlikely to have been a key factor driving Japanese automaker decisions. Another possible concern is that, if CAFE was binding on the industry as a whole, then we might expect substantial leakage (Japanese improvements enable fuel economy decreases from other automakers) if firms can trade compliance credits. This seems unlikely because the industry as a whole had compliance headroom in 2009, and trading was not introduced until 2011.

With regards to empirical identification, even if CAFE was important, our DID controls are likely to account for that because our treatment and control groups are both from the same manufacturers. Even so, one might be concerned that CAFE reforms could have differential impacts on trucks versus cars (which is possible because there was far more slack in the passenger car fleet than in light-duty trucks). This could potentially affect our estimates because our treatment and control group are not perfectly balanced between the fleets (there are slightly more light-duty trucks in the control).

To address this possibility, we include interactions between time fixed effects interacted with a car/truck indicator to allow for vehicle-type-specific time trends (columns 2 and 3 of Table 1). In column 3, we also add time fixed effects interacted with firm indicators to allow for automaker-specific time trends. The estimated treatment effect remains statistically significant and of similar magnitude after adding these controls, providing further support for the validity of our identification strategy.

In Table 2, we present additional robustness analyses. In addition to the granular time fixed effects included in Table 1, we incorporate more flexible time controls to further assess robustness. Column 1 includes time fixed effects interacted with an indicator for heavier vehicles, allowing for potentially different unobserved time-varying effects between lighter and heavier vehicles. Column 2 conducts a similar exercise using wheelbase, and Column 3 includes both sets of interactions.[6] In addition, Column 4 interacts time fixed effects with body style to allow each body style to experience distinct unobserved time-varying effects.[7] Although these highly granular time fixed effects may absorb some of the key identifying variation, we find that the DID estimates remain robust to their inclusion.

In Table 3, we provide an additional robustness check using a triple-difference design. Recall that, in Table A.2, we estimate the DID estimation for American automakers' vehicles in the U.S. market as a placebo test and find economically and statistically insignificant spillover effects. In the triple-difference estimation in Table 3, we augment Equation (1) by including both Japanese and American automakers and interacting the treatment variable (D_{jt}) with an indicator for Japanese firms.

For both Japanese and American automakers, we have treated vehicles (i.e., vehicles sold in both Japan and the United States) and untreated vehicles (i.e., vehicles sold in the United States

[6]We construct these indicator variables using the median values of vehicle weight and wheelbase as cutoff thresholds.

[7]See footnote 2 for a description of body style.

but not in Japan). Using this variation, we can interact time fixed effects with the treated group to control for potential unobserved time-varying factors specific to the treated group.[8] The key question is whether our estimate of the global spillover effect remains robust with these additional controls introduced by the triple-difference approach.

Columns 1–3 of Table 3 report results using the same baseline set of fixed effects as in Table 1, while additionally interacting time fixed effects with the treated group.[9] For example, column 3 includes model fixed effects as well as two types of time fixed effects interacted with the treated group, allowing vehicles sold in both Japan and the United States to exhibit different time patterns from those sold only in the United States. Furthermore, Table A.3 presents results using the four fixed-effect specifications reported in Table 2. Across all specifications, the triple-difference estimates indicate that the global spillover effect remains robust to these additional controls.

3.3 What Drives the Spillover Effects?

What drives the spillover effects documented in Section 3.1? In this section, we explore two potential mechanisms. First, our vehicle production data indicate that some models are produced in a single country and shipped to multiple markets, whereas others are produced separately in each market. We hypothesize that if cross-market cost complementarity is an important mechanism underlying attribute propagation, the magnitude of spillover effects may differ between these two types of models, which vary in the concentration of production locations.

To empirically test this hypothesis, we compile model-level production data that include production quantities and locations. Using these data, we construct a measure of the concentration of production locations as follows. For each model, we identify the production location that accounts for the highest total production quantity during our sample period. We then divide the production at this location by the model's total production across all locations. This measure equals one if a model is produced entirely in a single location and is lower when production is spread across multiple locations.

Second, our data in the pre-subsidy period reveal that some vehicle models exhibited similar fuel

[8]For example, if internationally sold vehicles are subject to different time-varying shocks than domestically sold vehicles, these additional time fixed effects absorb such variation.

[9]Note that "Year FE $\times$ Firm FE cannot be interacted with the treated vehicles because within firms, we obviously do not have both Japanese and American firms.

economy within a model across the U.S. and Japanese markets, while others showed considerable differences in fuel economy between the two countries, despite being sold under the same model name. This suggests that the degree of product differentiation within a model across the two markets was heterogeneous in the baseline period.

We hypothesize that pre-existing cross-market product differentiation may influence the magnitude of international spillover effects. Specifically, less-differentiated models (i.e., those with similar fuel economy across markets) were more likely designed and manufactured jointly for both markets. In contrast, more differentiated models (i.e., those with larger differences in fuel economy) were more likely tailored separately for each market. Based on this reasoning, we expect larger spillover effects for models with less pre-existing product differentiation.

To test this prediction, we construct a measure of cross-market product differentiation as follows. For each vehicle model in 2009, we compute the average fuel economy separately for the U.S. and Japanese markets and then take the absolute value of the log difference between the two.

In Table 4, we empirically test these predictions by interacting the treatment variable, D_{jt} in equation (1), with the concentration of production locations in column 1, the measure of cross-market product differentiation in column 2, and both variables jointly in column 3. We demean the interaction variables so that the coefficient on the main treatment variable captures the effect evaluated at the mean values of the interaction variables. We use the most conservative set of fixed effects employed in the final column of Table 2 and cluster standard errors at the model level. We also demean the interaction variables; therefore, the coefficient on the non-interacted treatment variable captures the average effect for vehicles evaluated at the mean values of the interaction variables.

In column 1, the positive coefficient on the interaction term suggests that spillover effects are larger for vehicle models with a higher concentration of production locations. This finding is consistent with cross-market cost complementarity as an important mechanism underlying attribute propagation. In column 2, the negative coefficient on the interaction term indicates that models with greater pre-existing product differentiation across markets exhibit smaller spillover effects. That is, we observe larger spillover effects for vehicles that have less cross-market differentiation. In column 3, we further find that both interaction effects remain strong when included simultaneously.

3.4 Potential Impacts on Other Product Attributes

The analysis thus far has focused on the spillover effects of the Japanese subsidy policy on fuel economy in the U.S. market. We can extend our DID framework in equation (1) to examine whether the policy also had spillover effects on other product attributes. In Table A.4, we apply our main DID specification to estimate treatment effects on additional vehicle characteristics in the U.S. market. We do not find statistically significant effects on product attributes other than fuel economy, suggesting that automakers' responses were primarily to improve fuel economy directly.

3.5 Potential Impacts on Product Entry and Exit

Recent studies in the international trade literature emphasize that firms, including automakers, may respond to policy shocks through adjustments in product entry and exit (Sabal, 2024). In our context, however, such a response is less likely because the Japanese subsidy policy targeted a single product attribute: fuel economy. As a result, automakers may have found it more cost-effective to adjust the fuel economy of existing models rather than engage in more costly product entry or exit decisions.

Nevertheless, we empirically test whether the Japanese subsidy policy affected product entry and exit behavior. For each model-year, we identify product entries and exits to calculate net entry counts, which we then plot separately for the treated and control groups in Figure A.1. The net entries are similar between the two groups and similar before and after the introduction of the Japanese subsidy policy. Thus, there is an absence of evidence that the subsidy differentially influenced net entry between the treatment and control groups.

In Table A.5, we also provide statistical evidence on entry, exist, and net entry by estimating DID regressions. The DID estimates indicate that the Japanese subsidy policy did not have statistically significant effects on entry, exit, and net entry, further supporting the view that automakers were likely to focus on adjusting the fuel economy of existing models in response to this policy.

3.6 Direct Policy Effects in the Japanese Market

A natural question is how large the spillover effect is relative to the policy's direct effect in the Japanese market. We lack a natural treatment and control group that are both within Japan—all vehicles were potentially eligible for the subsidy.

Instead, we can use the same treatment and control group as in our main analysis, but for the treated vehicles we examine their fuel economy in Japan. This provides a DID for fuel economy in Japan, where the identifying assumption is that, absent the policy, the fuel economy of the treated cars in Japan would have tracked the fuel economy of the control in the U.S. Practically, this is the same as estimating Equation (1), on the same sample, but using Japanese fuel economy for the treated observations.

We have two possible predictions. One is complete spillover, in which automakers make identical fuel economy improvements in Japan and the United States. Under this scenario, the direct treatment effect on fuel economy in Japan would be similar to the spillover effect on fuel economy in the United States in Section 3.1, where we find an improvement of 0.083 log points (8.65 percent). Another possibility is partial spillover, where the direct effect on fuel economy in Japan would be larger than the spillover effect in the United States.

Table 5 provides evidence consistent with partial spillover. Column 3 shows that the direct effect on fuel economy in Japan is a 0.225 log point (25.2 percent) improvement on average, which exceeds the spillover effect estimated for the U.S. market (an 8.65 percent improvement). The resulting spillover-to-direct ratio in terms of fuel economy improvements is therefore 0.34 (= 8.65 / 25.2). However, this ratio alone does not capture the relative environmental impacts, as it does not account for differences in reduced externalities, which we examine in the next section.[10]

3.7 Spillover Multiplier

The DID estimation results indicate that the Japanese policy's direct effect was a 25.2 percent improvement in fuel economy in Japan, whereas the spillover effect in the U.S. market was a 8.65 percent improvement.

Importantly, these estimates do not imply that the policy's environmental impact in the United States is 0.34 (= 8.65 / 25.2) of its impact in Japan, as environmental externalities depend not only

[10]Both the U.S. and Japanese fuel economy ratings systems experienced reforms during our sample period. Below, we account for average differences across the two systems when translating fuel economy into carbon emissions below. In the DID, we do not make any adjustments—we use the ratings that were shown to consumers in each year. We do this because the changes in the measurement systems in each country appear to track each other closely, as estimated by third-party tests engineering comparisons (Tietge, Díaz, Mock, German, Bandivadekar, and Ligterink, 2017). Adjusting for changes in the rating would thus cancel out in our DID.

on fuel economy improvements but also on sales volumes and vehicle miles traveled. First, the U.S. automobile market is substantially larger than that of Japan. Therefore, more vehicles in the US can be affected by the policy. Second, U.S. drivers travel substantially more miles per vehicle than Japanese drivers, resulting in more gasoline consumption per vehicle. The average annual miles traveled per vehicle in 2009 were 11,218 in the United States and 3,206 in Japan.[11] As a result, a given improvement in fuel economy may generate a larger reduction in environmental externalities in the United States.

To evaluate the policy's environmental impact in each country, we take the following steps. Our DID estimates provide the percentage change in fuel economy (miles per gallon) for affected vehicles. We convert these estimates into changes in gasoline consumption per mile (gallons per mile) and multiply them by the average annual miles driven per vehicle in each country to obtain the reduction in gasoline consumption.[12] We then translate the reduction in gasoline consumption into metric tons of CO_2 emissions avoided.[13]

We define the spillover multiplier of environmental impacts (ρ) as follows:

$$\begin{aligned}
\rho &\equiv \frac{\text{Japanese policy's environmental impacts in Japan and the U.S.}}{\text{Japanese policy's environmental impacts in Japan}} \\
&= 1 + \frac{\Delta\text{Externality per vehicle}_{US} \times Q_{US}}{\Delta\text{Externality per vehicle}_{JP} \times Q_{JP}} \\
&= 1 + \frac{0.28 \text{ tons of } CO_2 \times 5,395,182}{0.16 \text{ tons of } CO_2 \times 2,074,181} \\
&= 1 + \frac{1,494,166 \text{ tons of } CO_2 \text{ per year}}{337,831 \text{ tons of } CO_2 \text{ per year}} \\
&= 5.42, \qquad (2)
\end{aligned}$$

[11]These statistics are based on reports from the US Department of Transportation (FHA, 20018) and the Japan Automobile Manufacturers Association (JAMA, 2009).

[12]Our calculation assumes that Japanese starting fuel economy is 20% lower than the official rating in order to account for differences in fuel economy tests. Kühlwein, German, and Bandivadekar (2014) shows that the Japanese test has very similar average ratings to the ratings used for CAFE compliance, but US consumer label ratings (our data) are based on a modification that, according to the EPA, makes label ratings 20% lower than CAFE ratings (https://nepis.epa.gov/Exe/ZyPDF.cgi/P100IENB.PDF?Dockey=P100IENB.PDF). Tietge, Díaz, Mock, German, Bandivadekar, and Ligterink (2017) estimates that the US label ratings have minimal bias when compared to real world driving in this time period. Thus, we assume the US label ratings are accurate but Japan's ratings are 20% too optimistic.

[13]In doing our calculation, we abstract from a potential rebound effect—drivers may increase vehicle usage when fuel economy improves. This extension could be incorporated, but if proportional rebound effects are identical across the two countries, they cancel out in Equation 2 and have no impact on ρ.

where ΔExternality per vehicle denotes the policy-induced change in CO_2 emissions per vehicle, and Q denotes the quantity of affected vehicles. ΔExternality per vehicle is larger in the United States foremost because average annual miles traveled per vehicle are higher. Moreover, Q is larger in the United States because the affected models—those sold in both countries—have higher total sales in the U.S. market.

The spillover ratio of environmental impacts (ρ) is greater than one, implying that the Japanese policy's environmental impact abroad exceeds its domestic impact. This finding carries important policy implications. Standard analyses of environmental policies often focus exclusively on domestic effects, potentially leading to a substantial understatement of overall policy impacts.

There is one important limitation in our calculation of ρ based on the DID estimates. The calculation above focuses only on vehicles directly affected by the spillover effects of the fuel economy subsidy. What may be missing are potential equilibrium effects: vehicles that are not directly affected by the global spillover may nevertheless adjust their fuel economy in response to competitors' changes. In the next section, we develop a model of multinational automobile markets with global policy spillovers to incorporate these equilibrium effects into the calculation of ρ.

4 A Model of Multinational Car Markets with Global Policy Spillovers

In this section, we develop and estimate model of multinational firms with the potential for global policy spillovers. To do so, we extend a standard differentiated-product market model to incorporate firms selling products in multinational markets and incorporate firms' endogenous attribute choices. This allows us to estimate potential cross-market links in revenues and costs.

4.1 Demand

We follow Berry, Levinsohn, and Pakes (1995) to model a consumer's new car purchase with a random utility model. We estimate demand in Japan and the United States separately, allowing the demand systems to differ between the markets.

We use p_{jc} to denote price for product j in market c and x_{jc} for a vector of product characteristics for product j in market c. Conditional indirect utility of consumer i who purchases product j can be written by: $u_{ijc} = \beta_i x_{jc} + \alpha_i p_{jc} + \xi_{jc} + \epsilon_{ijc}$, where ξ_{jc} is unobserved factors at the market-product level and ϵ_{ijc} is unobserved factors at the market-product-consumer level. We assume ϵ_{ijc} is distributed type-I extreme value. The market share for product j in country c is:

$$s_{jc} = \int \frac{\exp(\beta_i x_{jc} + \alpha_i p_{jc} + \xi_{jc})}{\sum_{j'=0}^{J} \exp(\beta_i x_{j'c} + \alpha_i p_{j'c} + \xi_{j'c})} f(\mu_i) d\mu_i, \tag{3}$$

where $f(\mu_i)$ is the distribution of random-coefficients. The outside option is not to buy product $j = 1, ..., J$. This market share is usually unobservable from a dataset. A typical approach is to assume that s_{0c} is the number of consumers (households) in market c that did not buy any product j.

We begin by estimating demand using the standard logit model without random coefficients. In this specification, the preference parameters do not vary across consumers, allowing Equation (3) to be written in linear form as $\ln s_j - \ln s_0 = \beta x_{jc} + \alpha p_{jc} + \xi_{jc}$. An advantage of this approach is that it can be consistently estimated using linear instrumental variables methods with valid instruments. A key limitation, however, is that the standard logit model imposes restrictive substitution patterns through the Independence of Irrelevant Alternatives (IIA) assumption.

To address the issue with the IIA, we use a random-coefficient logit approach for our main specification. We allow heterogeneity in α with a log-normal distribution. An advantage of this approach is that it allows for flexible substitution patterns, less restrictive price elasticities, and heterogeneous consumer tastes. A key challenge is that nonlinear GMM estimation requires numerical simulation and does not guarantee convergence to a unique global optimum; therefore, careful implementation is necessary to obtain globally optimal estimates (Knittel and Metaxoglou, 2014; Conlon and Gortmaker, 2020).

4.2 Supply and Equilibrium

We describe the operating profit of multinational, multi-product firm f in each market as follows:

$$\begin{aligned} \text{Japan: } \pi_f &= \sum_{j \in J_f} \left[(p_j - c_j(e_j, x_j)) \cdot q_j \left(p_j - \tau_j(e_j), e_j, x_j \right) \right] \\ \text{US: } \tilde{\pi}_f &= \sum_{j \in \tilde{J}_f} \left[(\tilde{p}_j - \tilde{c}_j(\tilde{e}_j, \tilde{x}_j)) \cdot \tilde{q}_j \left(\tilde{p}_j, \tilde{e}_j, \tilde{x}_j \right) \right], \end{aligned} \tag{4}$$

where J_f denotes the set of cars sold by firm f; p_j is the price of car j; c_j is its marginal cost; e_j denotes fuel economy; x_j is a vector of other product attributes; q_j represents demand; and $\tau_j(e_j)$ is the fuel-economy subsidy in Japan. We use tildes to denote the corresponding variables in the U.S. market.

Firm f maximizes the joint profit from the two markets, with respect to prices and fuel economy:

$$\max_{p,e,\tilde{p},\tilde{e}} \pi_f^{\dagger} = \pi_f(p,e,x) + \tilde{\pi}_f(\tilde{p},\tilde{e},\tilde{x}) - \sum_{j\in J_f} FC(e_j,\tilde{e}_j), \tag{5}$$

where p, e, $\tilde{p}$, and $\tilde{e}$ are vectors of prices and fuel economy for all products. The function $FC(e_j,\tilde{e}_j)$ denotes a fixed cost of fuel economy, which we allow to depend on both e_j and $\tilde{e}_j$. In Section 5.3, we describe how we model this fixed cost to allow for cross-market complementarity.

Equation 5 implies that, in equilibrium, four first-order conditions—with respect to $(p_j, e_j, \tilde{p}_j, \tilde{e}_j)$—must be satisfied for each product j:

$$q_j + \sum_{k\in J_f}\left[(p_k - c_k)\frac{\partial q_k}{\partial p_j}\right] = 0, \tag{6}$$

$$-\frac{\partial c_j}{\partial e_j}q_j + (p_j - c_j)\left(\frac{\partial q_j}{\partial e_j} - \frac{\partial q_j}{\partial(p_j-\tau_j)}\frac{\partial \tau_j}{\partial e_j}\right) + \sum_{k\neq j\in J_f}\left[(p_k - c_k)\frac{\partial q_k}{\partial e_j}\right] = \frac{\partial FC(e_j,\tilde{e}_j)}{\partial e_j}. \tag{7}$$

$$\tilde{q}_j + \sum_{k\in \tilde{J}_f}\left[(\tilde{p}_k - \tilde{c}_k)\frac{\partial \tilde{q}_k}{\partial \tilde{p}_j}\right] = 0, \tag{8}$$

$$-\frac{\partial \tilde{c}_j}{\partial \tilde{e}_j}\tilde{q}_j + \sum_{k\in \tilde{J}_f}\left[(\tilde{p}_k - \tilde{c}_k)\frac{\partial \tilde{q}_k}{\partial \tilde{e}_j}\right] = \frac{\partial FC(e_j,\tilde{e}_j)}{\partial \tilde{e}_j}. \tag{9}$$

Equations 6 and 8 are the first-order conditions with respect to prices, which are standard in the literature on differentiated product markets. For each firm f in each market, these conditions yield a system of J_j equations in J_j unknown marginal costs, allowing us to recover marginal costs given demand estimates.

Equations 7 and 9 are the first-order conditions with respect to fuel economy.[14] The left-hand side of Equation 9 represents the net marginal revenue from an increase in fuel economy. $\sum_{k\in \tilde{J}_f}(\tilde{p}_k - \tilde{c}_k)\frac{\partial \tilde{q}_k}{\partial \tilde{e}_j}$ captures the marginal revenue, while $-\frac{\partial \tilde{c}_j}{\partial \tilde{e}_j}\tilde{q}_j$ reflects the increase in marginal cost. This first-order condition therefore implies that firms equate the net marginal revenue with

[14] Our approach follows Fan (2013) in modeling endogenous product attributes, as in her analysis of newspapers.

respect to fuel economy—the left-hand side—with the marginal fixed cost—the right-hand side—when endogenously choosing the optimal level of fuel economy.

Each element of Equation 9 can be obtained from data or the estimated demand and marginal cost functions. Once we obtain these, we can estimate a function of slope of fixed cost, $\frac{\partial FC(e_j,\tilde{e}_j)}{\partial \tilde{e}_j}$, with a parametric assumption. We will discuss this estimation strategy in Section 5.3.

Compared to Equation 9 for the U.S. market, Equation 7 for the Japanese market includes an additional term, $-\frac{\partial q_j}{\partial (p_j-\tau_j)} \cdot \frac{\partial \tau_j}{\partial e_j}$, for j. This term captures the marginal effect of fuel economy e_j on the subsidy $\tau_j(e_j)$ and the subsidy's effect on demand q_j. This term reflects how a change in e_j influences the level of the subsidy, thereby indirectly affecting consumer demand in Japan.[15]

In Section 5, we use our data and policy-induced variation to estimate the model. We then use the estimated model to conduct counterfactual simulations in Section 6. In these simulations, the four first-order conditions in Equations 7–8 play a central role. To illustrate the mechanism, consider a change in the subsidy τ_j and the resulting new equilibrium. The direct effect of the subsidy change enters only the fuel-economy first-order condition in Japan (Equation 7). However, any induced change in fuel economy in Japan can affect the optimal level of fuel economy in the U.S. (Equation 9) through the slope of fixed cost, provided that e_j and $\tilde{e}_j$ are complements in the slope of fixed cost function. These adjustments in optimal fuel economy then feed into the price first-order conditions in Equations 6 and 8, leading firms to choose new equilibrium levels of both prices and fuel economy.

Our structural model does not explicitly model U.S. Corporate Average Fuel Economy (CAFE) as a constraint. We believe this is a reasonable approximation for our setting for several reasons. First, the CAFE passenger car standard had been frozen at 27.5 mpg since 1990, and by 2009, in the face of years of rising gasoline prices, the industry-wide fleet averages exceeded the standard by substantial margins: 17 percent for domestic passenger cars, 23 percent for imported passenger cars, and 8 percent for light trucks.[16] Second, and most relevant for our analysis, every Japanese manufacturer in our sample was in compliance with the standard across all fleet categories in 2009, typically by wide margins. For example, Toyota's import passenger car fleet averaged 39.4 mpg

[15]The subsidy schedule is a step function of fuel economy and is non-differentiable at the cutoff points. To address this issue, we approximate it using a piecewise linear function.

[16]We take these figures directly from the National Highway Safety Administration's compliance report: https://www.nhtsa.gov/sites/nhtsa.gov/files/performance-summary-report-12152014-v2.pdf.

against a 27.5 mpg standard, and Honda's domestic passenger car fleet averaged 34.3 mpg. General Motors and Ford also had headroom at this time. The non-compliant manufacturers were European luxury brands (e.g., Daimler, Jaguar Land Rover, Porsche), which historically chose to pay modest civil penalties rather than comply; these firms have small U.S. market shares and are not the focus of our analysis. Thus, it seems plausible to argue that CAFE was not a binding concern in the period of our focus.

5 Estimation of the Model

In this section, we estimate the model presented in Section 4. We begin by estimating demand in Section 5.1, followed by the estimation of marginal costs in Section 5.2, and slope of fixed costs in Section 5.3. We then use the estimated model to conduct counterfactual policy simulations in Section 6.

5.1 Demand Estimation Results

Our demand estimation follows the standard approach for differentiated products (Berry, Levinsohn, and Pakes, 1995). A key distinction in our setting is that fuel economy is an endogenous product attribute in our model described in Section 4. Because firms endogenously choose both prices and fuel economy, both variables may be correlated with the unobserved product characteristics in the demand equation. To address this potential endogeneity, we construct two sets of instrumental variables (IVs). Our approach is closely related to Reynaert (2021), which implements an IV strategy for endogenous vehicle characteristics.

The first set of our IVs consists of standard BLP-type instruments based on exogenous product characteristics, which exclude fuel economy. Following Gandhi and Houde (2020), we construct quadratic differentiation instruments using exogenous attributes. These instruments measure the extent to which a product differs from other products sold by the same firm and from products sold by rival firms along each exogenous characteristic.

The second set of our IVs exploits policy-induced variation in fuel economy. Following Ito and Sallee (2018), we leverage a unique feature of the Japanese fuel-economy subsidy to construct an instrument for fuel economy. To qualify for the subsidy, a vehicle's fuel economy (e_j) had to exceed a target level defined by a nonlinear step function presented in Figure A.2. This design generated variation in the ease or difficulty of qualifying for the subsidy, thereby inducing policy-driven changes in e_j during the subsidy period. Because the subsidy was introduced in 2009, we construct the instrument as $\Delta e_j = e_j^{\text{target}} - e_{j,2008}$, which captures the gap between the policy target and the vehicle's pre-policy fuel economy. This pre-determined gap predicts subsequent adjustments in fuel economy but is plausibly exogenous to contemporaneous demand shocks.

Figure A.2 visually illustrates the policy-induced variation. Each dot represents a vehicle's fuel economy and weight in 2008. For vehicles that qualified for the subsidy by 2012, we plot vectors connecting their initial (2008) positions to their final (2012) positions. The figure shows that the distance to the subsidy cutoff (i.e., Δe_j) explains substantial variation in the magnitude of fuel-economy improvements. We exploit this variation to instrument for the endogenous attribute, fuel economy.[17]

As described in Knittel and Metaxoglou (2014) and Conlon and Gortmaker (2020), estimating the random-coefficients demand model in Equation 3 requires careful implementation because minimizing its nonlinear GMM objective function involves a non-convex optimization problem. Following Conlon and Gortmaker (2020), we use the L-BFGS-B optimization algorithm and implement several procedures to ensure robustness. First, we impose a tight convergence tolerance for the numerical optimization.[18] Second, we initialize the algorithm from 100 distinct starting values to assess sensitivity to initial conditions. Third, we verify that the final estimates satisfy both the first-order and second-order optimality conditions.

Table 6 reports the demand estimation results for Japan and the United States. We estimate random-coefficients on prices (α_i) with the log-normal distribution such that $\alpha_i = -\exp(\pi + \sigma v_i)$, where v_i is distributed as the standard normal distribution. We report π, σ, and the median of α_i. Asymptotically robust standard errors are given in parentheses.

In both markets, consumers value fuel economy, horsepower, vehicle weight and lower prices.

[17] We apply the same approach to construct an instrument for fuel economy in the United States. Although the subsidy was implemented only in Japan, attribute propagation implies that the policy-induced incentives indirectly influenced fuel economy in the U.S. market. Specifically, we construct $\Delta\tilde{e}j = e_j^{\text{target}} - \tilde{e}_{j,2008}$, where $\tilde{e}_{j,2008}$ denotes a vehicle's fuel economy in the United States in 2008. Thus, $\Delta\tilde{e}_j$ measures the distance between the vehicle's 2008 U.S. fuel economy and the Japanese subsidy cutoff, as if the subsidy had applied in the United States. We confirm that this instrument generates a strong first stage in both Japan and the United States.

[18] We use a tolerance level of 10^{-14} for convergence in the nested fixed point algorithm that equates predicted market shares to observed market shares, and a tolerance level of 10^{-8} for convergence of the GMM objective function.

The parameter σ represents the standard deviation of the log-normal random coefficient on price and indicates substantial unobserved heterogeneity in price sensitivity. Figure A.3 illustrates the implied distribution of the price coefficient to visualize this heterogeneity in price elasticity.

Overall, the demand estimates suggest that preference parameters are broadly similar across the two markets. One notable exception is the coefficient on fuel economy. Our results indicate that consumers in the United States place slightly greater value on fuel economy than consumers in Japan, potentially because U.S. drivers travel substantially more miles than Japanese drivers, as discussed in Section 3.7.

5.2 Marginal Cost Estimation Results

As discussed in Section 4.2, the first order conditions with respect to prices in Equations 6 and 8 yield a system of J_f equations in J_f unknown marginal costs for firm f, allowing us to recover the marginal costs (c_j) given the estimated demand system.

We regress the recovered marginal costs c_j on product attributes to estimate the marginal cost function. We estimate it separately for each market to allow for cross-market heterogeneity. To address potential endogeneity, we use the quadratic differentiation instruments using exogenous attributes and the policy-induced instruments for fuel economy described in Section 5.1. We use these instruments to estimate a two-step GMM, weighting by sales volumes and clustering standard errors at the model level.

Table 7 reports the marginal cost estimation results for each market, with and without firm fixed effects. With firm fixed effects, the estimated coefficient on vehicle weight is similar across the two countries, while the coefficient on fuel economy is larger in the United States. This pattern suggests that a unit increase in fuel economy leads, on average, to a larger increase in marginal cost in the United States than in Japan. In contrast, our result indicates that a unit increase in horsepower leads, on average, to a larger increase in marginal cost in Japan than the United States.

5.3 Slope of Fixed Cost Estimation Results

Our approach builds on the estimation of the slope of fixed costs with respect to endogenous product attributes in Fan (2013) and Barwick, Kwon, and Li (2024a). Our approach extends this method to incorporate cross-market complementarity in the slope of fixed costs.

Firm f's first order conditions with respect to fuel economy—Equations 7 and 9—provides an estimate of the marginal fixed cost with respect to an improvement in fuel economy, $\frac{\partial FC(e_j,\tilde{e}_j)}{\partial e_j}$ and $\frac{\partial FC(e_j,\tilde{e}_j)}{\partial \tilde{e}_j}$. The left-hand sides of these equations can be calculated given data and parameter estimates from the demand and marginal cost estimation. We can then estimate the slope of fixed cost function if we assume a parametric functional form.

We assume that firms face the following fixed cost function for improving fuel economy:

$$FC(e_j, \tilde{e}_j) = \gamma + (\gamma_0 e_j + \gamma_1 e_j^2) + (\tilde{\gamma}_0 \tilde{e}_j + \tilde{\gamma}_1 \tilde{e}_j^2) + \gamma_2 e_j \tilde{e}_j, \tag{10}$$

where e_j and $\tilde{e}_j$ denote fuel economy in Japan and the United States, respectively. This specification implies that firms incur a quadratic cost when improving fuel economy. The final term γ_2 captures a potential cost complementarity between fuel economy choices in Japan and the United States.

Recall that Equations 7 and 9 characterize the marginal fixed costs (the slope of fixed costs), rather than the fixed cost itself. We therefore take derivatives of Equation 10 with respect to fuel economy in Japan (e_j) and the United States ($\tilde{e}_j$):

$$\frac{\partial FC(e_j, \tilde{e}_j)}{\partial e_j} = \gamma_0 + 2\gamma_1 e_j + \gamma_2 \tilde{e}_j \tag{11}$$

$$\frac{\partial FC(e_j, \tilde{e}_j)}{\partial \tilde{e}_j} = \tilde{\gamma}_0 + 2\tilde{\gamma}_1 \tilde{e}_j + \gamma_2 e_j. \tag{12}$$

We estimate these equations to recover the parameters γ_1 and γ_2, controlling for firm fixed effects (which absorb γ_0) to account for unobserved heterogeneity across firms. The key parameter of interest is γ_2, which governs the degree of scope economies in fuel-economy choices. If γ_2 is negative, an improvement in fuel economy in the U.S. lowers the cost of improving fuel economy in Japan for the same model, and vice versa. To address the potential endogeneity of fuel-economy choices, we use the policy-induced instruments described in Section 5.1 as instrumental variables for e_j and $\tilde{e}_j$. Our specification allows γ_0 and $\tilde{\gamma}_0$ to vary across markets and automakers. To improve precision, we restrict γ_1 to be the same across markets. Finally, we allow γ_2 to vary with the concentration of production locations described in Section 3.3, in order to examine whether cross-market complementarity differs between models produced in a single country and shipped to multiple markets and those produced separately in each market.

Table 8 reports the estimated slopes of the fixed-cost function. All columns include country fixed effects, and columns 2 and 4 further interact these fixed effects with firm fixed effects. Recall that γ_1 is the coefficient on the quadratic term in model j's fuel economy in Equation 10. All estimates of γ_1 are positive, which implies that the fixed cost of improving fuel economy is convex in fuel economy.

In Equation 10, γ_2 is the coefficient on the interaction between model j's fuel economy in one market and the corresponding model's fuel economy in another market. Estimates of γ_2 are statistically significant and negative in all specifications, which is evidence of cross-market cost complementarity in firms' fuel-economy choices. That is, an improvement in fuel economy in Japan for vehicle j reduces the slope of fixed cost of improving fuel economy for the corresponding model in the United States, and vice versa. Therefore, when firms respond to Japan's fuel-economy subsidy by improving a model's fuel economy in Japan, the corresponding model in the United States experiences a reduction in the slope of fixed cost of improving fuel economy. Furthermore, columns 3 and 4 show that the magnitude of cross-market cost complementarity is larger for vehicles with a higher concentration of production locations. This mechanism provides a key explanation for global policy spillover effects.

6 Counterfactual Policy Simulation

To investigate the welfare impact of the global policy spillover, we use our structural model in Section 4 and parameter estimates from Section 5 to simulate two scenarios. The first is the actual scenario, where we include the fuel-economy subsidy policy in the Japanese market. The second is a counterfactual scenario, where we remove the fuel-economy subsidy policy and compute a new equilibrium.

6.1 Simulation Algorithm

In our policy simulation, we first introduce a counterfactual policy environment (e.g., removing Japan's fuel economy subsidy). Firms then endogenously choose four variables for each vehicle j—prices and fuel economy in Japan (p_j, e_j) and in the United States $(\tilde{p}_j, \tilde{e}_j)$—by solving the first-order conditions (FOCs) in Equations 8–7, yielding a new equilibrium. We allow firms to endogenously choose these four variables for all vehicles, including those sold in both countries and those sold only in one country.

Solving the four first-order conditions simultaneously is computationally intensive due to the large number of products produced by multi-product firms and the presence of nonlinear equilibrium conditions, including a random-coefficients demand system. We therefore solve the first-order conditions using the following iterative procedure.

In the first iteration, we initialize the algorithm using the observed values of p_j, e_j, $\tilde{p}_j$, and $\tilde{e}_j$ from the data. Within the iteration, we treat these values as given and solve the first-order conditions in Equations 7–8 separately. For example, we solve Equation 7 with respect to fuel economy in Japan (e_j), holding fixed the other three endogenous variables, p_j, $\tilde{p}_j$, and $\tilde{e}_j$. Similarly, we solve Equation 9 with respect to fuel economy in the United States ($\tilde{e}_j$), holding fixed p_j, $\tilde{p}_j$, and e_j.

Solving all four first-order conditions in this manner yields an updated set of p_j, e_j, $\tilde{p}_j$, and $\tilde{e}_j$. At the end of the iteration, we update the values of these endogenous variables, as well as demand and cost functions, which depend on them.

In the subsequent iterations, we repeat this procedure: each first-order condition is solved separately, taking the remaining endogenous variables from the previous iteration as given. At the end of each iteration, we update prices, fuel economy, demand, and costs, and proceed to the next iteration. We continue until the algorithm converges to a new equilibrium. We verify that this iteration process lowers the objective function's value over iterations—we show it in Figure A.4—and converge to a new counterfactual equilibrium by approximately 100 interactions.

6.2 Counterfactual Policy Simulation Results

Table 9 reports the counterfactual policy simulation results based on the structural model described in Section 4 and the parameter estimates from Section 5. Column 1 of Panel A presents the equilibrium when the fuel economy subsidy is in place in the Japanese market. Column 2 reports the counterfactual equilibrium in which the subsidy is removed. Columns 3 and 4 report the differences between the two scenarios in levels and percentages, respectively.

We report sales-weighted average fuel consumption (gallons per 100 miles) separately for all vehicles, vehicles that received the subsidy, and other vehicles in Japan.[19] The subsidized vehicles are those that receive the subsidy in the observed equilibrium. For the United States, we report the results for all vehicles, spillovered vehicles, and other vehicles. The spillovered vehicles are vehicle models that received the subsidy in Japan and also were sold in the United States. As discussed in Section 3.7, vehicles not directly affected by the subsidy may nevertheless adjust fuel economy in response to competitors' changes, generating indirect equilibrium effects.

For the subsidized vehicles in Japan and spillovered vehicles in the United States, we find simulation results that are consistent with our findings from the DID analysis in Sections 3.1 and 3.6. For these vehicles, on average, the subsidy in Japan improves fuel consumption by 21.86% in Japan, while generating a spillover effect of an 7.45% improvement in the U.S. market. Indirect equilibrium effects are smaller than direct effects at the per-vehicle level. In Japan, the indirect effect on other vehicles is a 3.29% increase in fuel consumption, whereas in the United States the indirect effect is a 2.21% reduction in fuel consumption.

In Panel B, we incorporate all of these effects to calculate the CO_2 emissions reductions induced by the subsidy in Japan. Our estimates suggest that the subsidy resulted in CO_2 emissions reductions of 0.75 megatonnes per year in Japan and a 2.27 megatonnes per year in the US. This translates into a spillover multiplier of the policy's environmental impacts (ρ) equal to 4.04 ($= 1 + 2.27/0.75$). This suggests that while accounting for indirect equilibrium effects is important, it does not substantially change our conclusions—while the Japanese subsidy policy reduces CO_2 emissions in both Japan and the United States, the resulting reductions in the United States are substantially larger than the domestic reductions in Japan. As such, abstracting from the global spillover effect could considerably understate policy impacts.

7 Conclusion

In a globalized economy, a country's domestic policies can generate global spillover effects through products designed and manufactured by multinational firms. In this paper, we study this phe-

[19] We report fuel consumption rather than fuel economy in Panel A because fuel consumption is the relevant variable for calculating CO_2 emissions in Panel B. Note that our DID estimation uses log fuel economy (miles per gallon) as the dependent variable, and log fuel consumption is simply the negative of log fuel economy. Therefore, expressing the results in terms of fuel consumption instead of fuel economy would yield exactly the same estimates with the signs of the treatment effects reversed.

nomenon, which we label attribute propagation, in the context of environmental regulation in the automobile market. To quantify attribute the significance of attribute propagation for environmental outcomes, we define the spillover multiplier of environmental impacts. Our study contributes novel methods and a first empirical quantification of these effects, which are related to the notion of the California effect (Vogel, 1995) and Brussels effect (Bradford, 2020).

We find that Japan's fuel economy subsidy led to significant improvements in the fuel economy of vehicles sold in the U.S. market, thereby generating global environmental benefits. We develop a model of multinational automobile markets to examine how cross-market linkages and costs give rise to such global spillovers. Using the estimated model, we conduct counterfactual policy simulations to quantify the environmental benefits and welfare effects of these global policy spillovers, accounting for equilibrium effects, namely how other non-treated vehicles change their fuel economy and prices. Our structural analysis confirms the significance of attribute propagation.

The economic significance of attribute propagation hinges on several conditions. First, the policy-imposing market must be large enough relative to the firm's global operations that firms find it worthwhile to adjust product attributes in response to the policy. Second, there must be meaningful economies of scope in product design across markets, so that attribute changes in one market lower the cost of similar changes elsewhere. Third, the receiving market must be large enough—both overall and in terms of the market share of affected products—that the propagated attribute changes have meaningful welfare or environmental consequences. These conditions were met in our setting, and we expect them to hold in other contexts where multinational firms face significant policy shocks in major markets—such as European Union regulations affecting products sold globally—making attribute propagation a consideration that policy evaluations should not ignore. In addition to these conditions, in our context a major factor amplifying the spillover multiplier of environmental benefits is that U.S. vehicles are driven many more miles per year.

We study one salient and important market and focus on environmental policy and outcomes. Attribute propagation could have similar significance for other policies or preference shocks. Our paper provides one potential roadmap for studying this phenomenon in other contexts.

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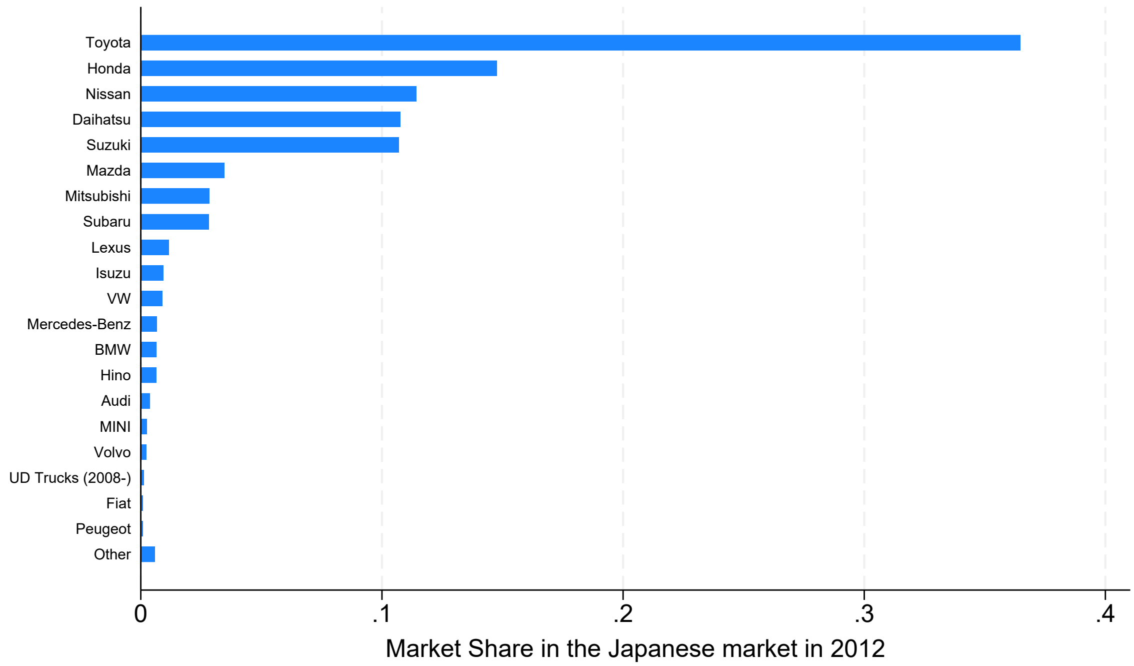
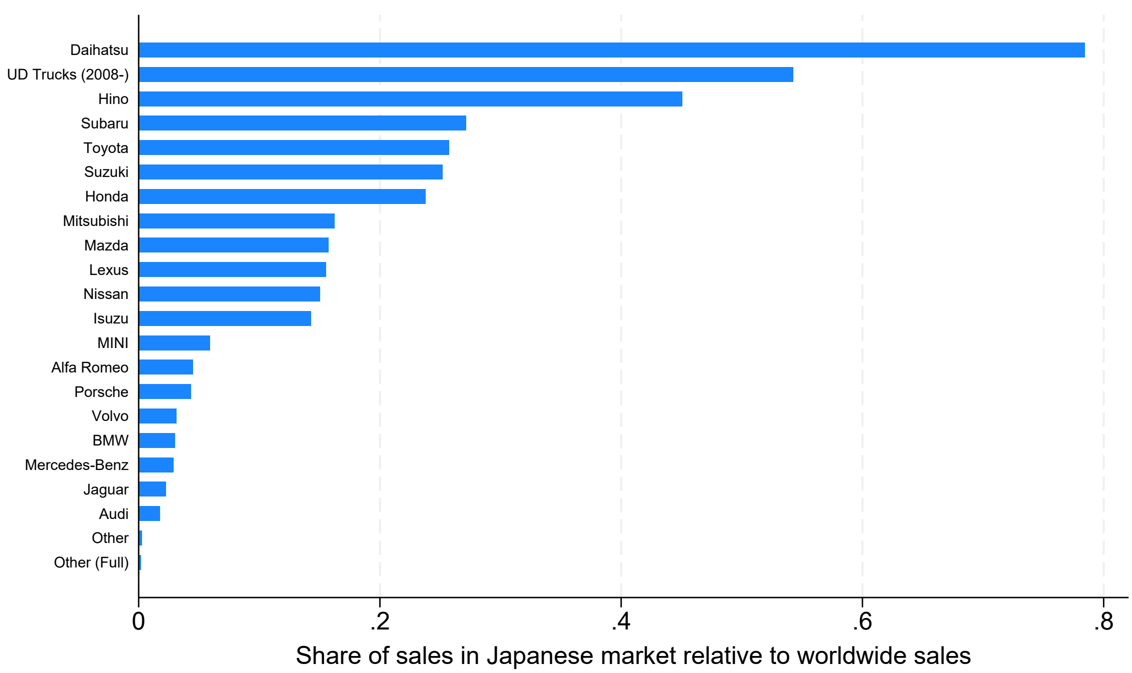
Figures and Tables

Figure 1: Market Shares

Panel A: Market Share in the Japanese market in 2012

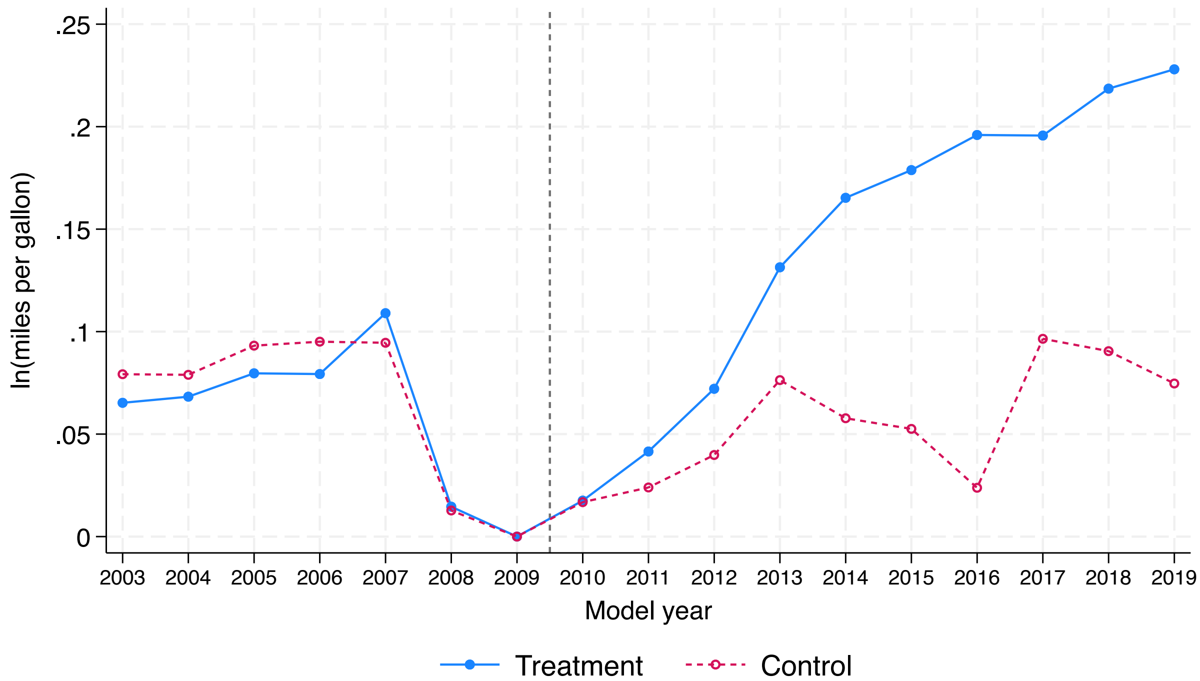


Panel B: Each firm's Japanese market share relative to its worldwide sales



Note: This figure shows market shares calculated using sales quantity data from MarkLines described in Section 2.2.

Figure 2: Average Fuel Economy of Japanese Firms' Vehicles in the U.S. Market



Note: This figure shows the sales-weighted average log fuel economy for the two groups described in Section 3.1. The figure includes all Japanese automakers (Honda, Isuzu, Lexus, Mazda, Mitsubishi, Nissan, Subaru, Suzuki, and Toyota). Each dot shows the log of fuel economy in the US auto market for each group, normalized at their 2009 level so that it shows the changes in the log of fuel economy relative to 2009. The treatment group includes Japanese automakers' vehicles that were sold in both the United Sates and Japan. The control group includes Japanese automakers' vehicles that were sold in the United Sates but not in Japan.

Table 1: Global Spillover Effects of Japan's Fuel-Economy Subsidy on the US Market

Dependent Variable: Log Fuel Economy

	(1)	(2)	(3)
Treated × Post	0.073	0.090	0.083
	(0.024)	(0.022)	(0.026)
N	9,098	9,098	9,098
Model FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Year × Truck FE	No	Yes	Yes
Year × Firm FE	No	No	Yes

Note: This table shows the OLS regression results of equation (1) desribed in Section 3.1. The dependent variable is the log of fuel economy (miles per gallon) at the make-model-trim level between model years 2003 and 2019. During this period, 94 unique models were sold in both markets, while 42 unique models were sold in the United States but not in Japan. All regressions are weighted by the average annual sales. Standard errors are clustered at the model level. The data include all vehicles sold by Japanese automakers in the US automobile market.

Table 2: Robustness Analysis of the Difference-in-Differences Estimation

Dependent Variable: Log Fuel Economy

	(1)	(2)	(3)	(4)
Treated × Post	0.097	0.105	0.106	0.071
	(0.028)	(0.030)	(0.031)	(0.026)
N	9,098	9,098	9,098	9,059
Model FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Year FE × Truck FE	Yes	Yes	Yes	Yes
Year FE × Firm FE	Yes	Yes	Yes	Yes
Year FE × Higher-weight FE	Yes	No	Yes	Yes
Year FE × Higher-wheelbase FE	No	Yes	Yes	Yes
Year FE × Body-style FE	No	No	No	Yes

Note: This table presents the robustness analysis described in Section 3.2. The dependent variable is the log of fuel economy (miles per gallon) at the make-model-trim level between model years 2003 and 2019. During this period, 94 unique models were sold in both markets, while 42 unique models were sold in the United States but not in Japan. All regressions are weighted by the average annual sales. Standard errors are clustered at the model level. The data include all vehicles sold by Japanese automakers in the US automobile market.

Table 3: Robustness Analysis Using Triple-Difference Estimation
Dependent Variable: Log Fuel Economy

	(1)	(2)	(3)
Treated × Post × Japanese Automakers	0.098	0.101	0.138
	(0.037)	(0.034)	(0.041)
Observations	30,665	30,665	30,665
Model FE	Yes	Yes	Yes
Year FE × Treated FE	Yes	Yes	Yes
Year FE × Treated FE × Truck FE	No	Yes	Yes
Year FE × Firm FE	No	No	Yes

Note: This table presents the triple-difference estimation results described in Section 3.2. The dependent variable is the log of fuel economy (miles per gallon) at the make-model-trim level between model years 2003 and 2019. All regressions are weighted by the average annual sales. Standard errors are clustered at the model level. The data include all vehicles sold by Japanese automakers (Honda, Isuzu, Lexus, Mazda, Mitsubishi, Nissan, Subaru, Suzuki, and Toyota) and those sold by American automakers in the US automobile market (Buick, Cadillac, Chevrolet, Chrysler, Dodge, Fisker, Ford, GMC, Hummer, Jeep, Lincoln, Mercury, Oldsmobile, Pontiac, Saturn, Tesla, and Wheego).

Table 4: What Drives Global Spillover Effects?

Dependent Variable: Log Fuel Economy

	(1)	(2)	(3)
Treated × Post	0.083	0.096	0.108
	(0.021)	(0.025)	(0.023)
Treated × Post × Concentration of production locations	0.141		0.144
	(0.074)		(0.077)
Treated × Post × Differentiation across markets		-0.185	-0.194
		(0.074)	(0.073)
Observations	8,459	9,059	8,459

Note: This table shows the OLS regression results of equation (1) with interactions between the treatment variable, D_{jt} in equation (1), with the concentration of production locations and the measure of cross-market product differentiation described in Section 3.3. To construct the concentration of production locations for each model, we identify each model's production location that accounts for the highest total production quantity during our sample period. We then divide the production at this location by the model's total production across all locations to make this measure. We also construct a measure of cross-market product differentiation as follows. For each vehicle model in 2009, we compute the average fuel economy separately for the U.S. and Japanese markets and then take the absolute value of the log difference between the two. All columns include the most conservative set of fixed effects employed in the final column of Table 2. Standard errors are clustered at the model level. The data include all vehicles sold by Japanese automakers in the US automobile market.

Table 5: Direct Effects of the Japanese Fuel-Economy Subsidy in Japan

Dependent variable: log fuel economy

	(1)	(2)	(3)
Treated × Post	0.203	0.276	0.225
	(0.081)	(0.125)	(0.115)
N	12,812	12,810	12,810
Model FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Year × Truck FE	No	No	Yes
Year × Make FE	No	Yes	Yes

Note: This table shows the OLS regression results in Section 3.6. The dependent variable is the log of fuel economy (miles per gallon) at the make-model-trim level between model years 2003 and 2019. All regressions are weighted by the average annual sales. Standard errors are clustered at the model level. The data include all vehicles sold by Japanese automakers in the US automobile market.

Table 6: Demand Estimation Results

	(1)	(2)
	Japan	US
Fuel economy (Miles per gallon)	0.117	0.244
	(0.009)	(0.032)
Horsepower	0.011	0.021
	(0.002)	(0.004)
Vehicle weight (1,000kg)	3.510	2.617
	(0.308)	(0.282)
Price/income (USD): Median coefficient	-18.51	-17.35
	(6.86)	(5.28)
Random-coefficient π	2.918	2.854
	(0.371)	(0.304)
Random-coefficient σ	1.079	0.641
	(0.190)	(0.093)
Observations	2,142	1,469

Note: This table shows the demand estimation results of our structural model in Section 5.1. We estimate random-coefficients on prices (α_i) with the log-normal distribution such that $\alpha_i = -\exp(\pi + \sigma v_i)$, where v_i is distributed as the standard normal distribution. We report π, σ, and the median of α_i. Asymptotically robust standard errors are given in parentheses.

Table 7: Marginal Cost Estimation Results

	Japan		US	
	(1)	(2)	(3)	(4)
Fuel economy (MPG)	314.89	416.56	926.83	703.99
	(15.79)	(16.82)	(96.41)	(67.46)
Horsepower	200.64	111.97	131.50	85.13
	(5.08)	(4.85)	(4.60)	(3.49)
Vehicle weight (kg)	5.68	14.97	13.26	12.47
	(0.74)	(0.68)	(1.11)	(0.84)
Firm FE	No	Yes	No	Yes
Observations	2142	2142	1469	1469

Note: This table shows the marginal cost estimation results described in Section 5.2. We use the quadratic differentiation instruments using exogenous attributes and the policy-induced instruments for fuel economy described in Section 5.1 to estimate a two-step GMM, weighting by sales volumes and clustering standard errors at the model level.

Table 8: Slope of Fixed Cost Estimation Results

	(1)	(2)	(3)	(4)
γ_1	0.897	0.853	1.149	0.816
	(0.040)	(0.080)	(0.077)	(0.086)
γ_2	-0.217	-0.321	-0.482	-0.236
	(0.041)	(0.076)	(0.081)	(0.077)
$\gamma_2 \times$ Concentration of production locations			-2.388	-1.193
			(0.279)	(0.245)
Country FE	Yes	Yes	Yes	Yes
Firm FE $\times$ Country FE	No	Yes	No	Yes

Note: This table shows the slope of fixed cost estimation results described in Section 5.3. We use the policy-induced instruments for fuel economy described in Section 5.1 to estimate Equation (11) with a two-step GMM, weighting by sales volumes and clustering standard errors at the model level.

Table 9: Counterfactual Policy Simulation Results

Panel A: Average fuel consumption (gallons per 100 miles)

	Actual	Counterfactual (no subsidy in Japan)	Impacts of the subsidy	
			Levels	% changes
Japan: All vehicles	2.27	2.61	-0.34	-13.02
Japan: Subsidized vehicles	1.93	2.47	-0.54	-21.86
Japan: Other vehicles	3.01	2.91	0.10	3.39
US: All vehicles	4.13	4.28	-0.14	-3.36
US: Spillovered vehicles	3.74	4.04	-0.30	-7.45
US: Other vehicles	4.25	4.35	-0.10	-2.21

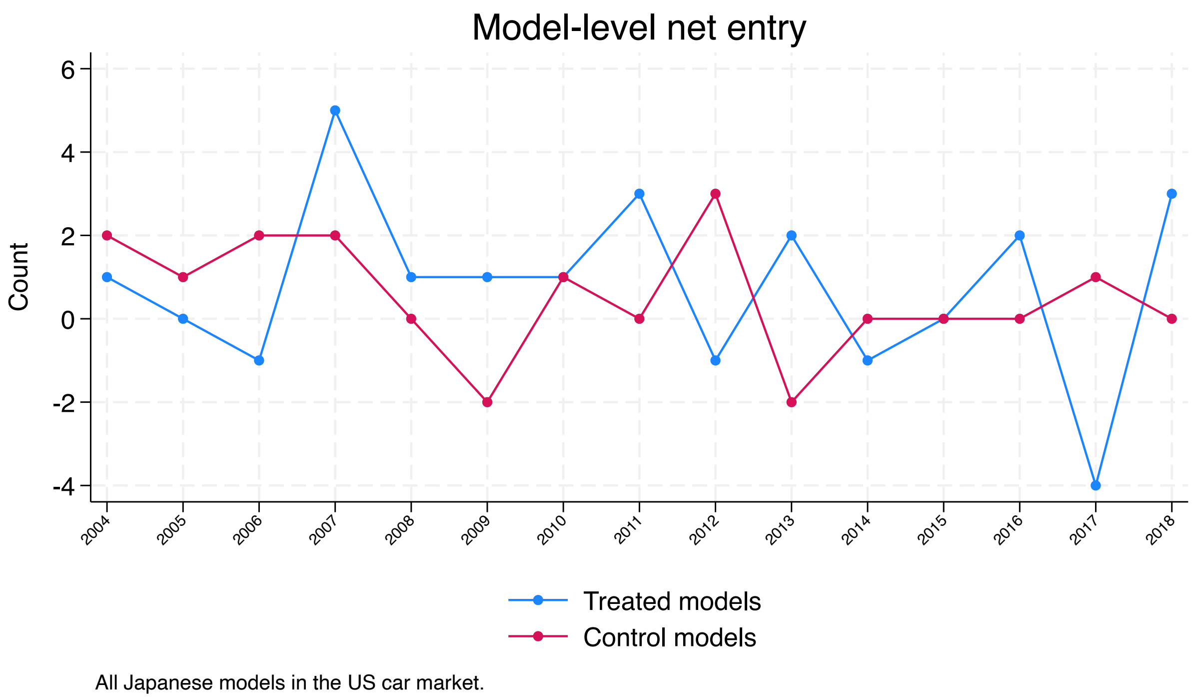
Panel B: CO_2 emissions reductions (megatonnes/year) and spillover multiplier (ρ)

Emissions reductions in Japan	Emissions reductions in the US	Spillover multiplier (ρ)
0.75	2.27	4.04

Note: This table presents the counterfactual simulation results described in Section 6. Panel A reports sales-weighted average fuel consumption (gallons per 100 miles) under the Actual scenario (with Japan's fuel-economy subsidy) and the Counterfactual scenario (without the subsidy). Panel B reports the policy's effects on CO_2 emissions reductions (megatonnes per year) and the spillover multiplier of environmental impacts defined in Section 3.7.

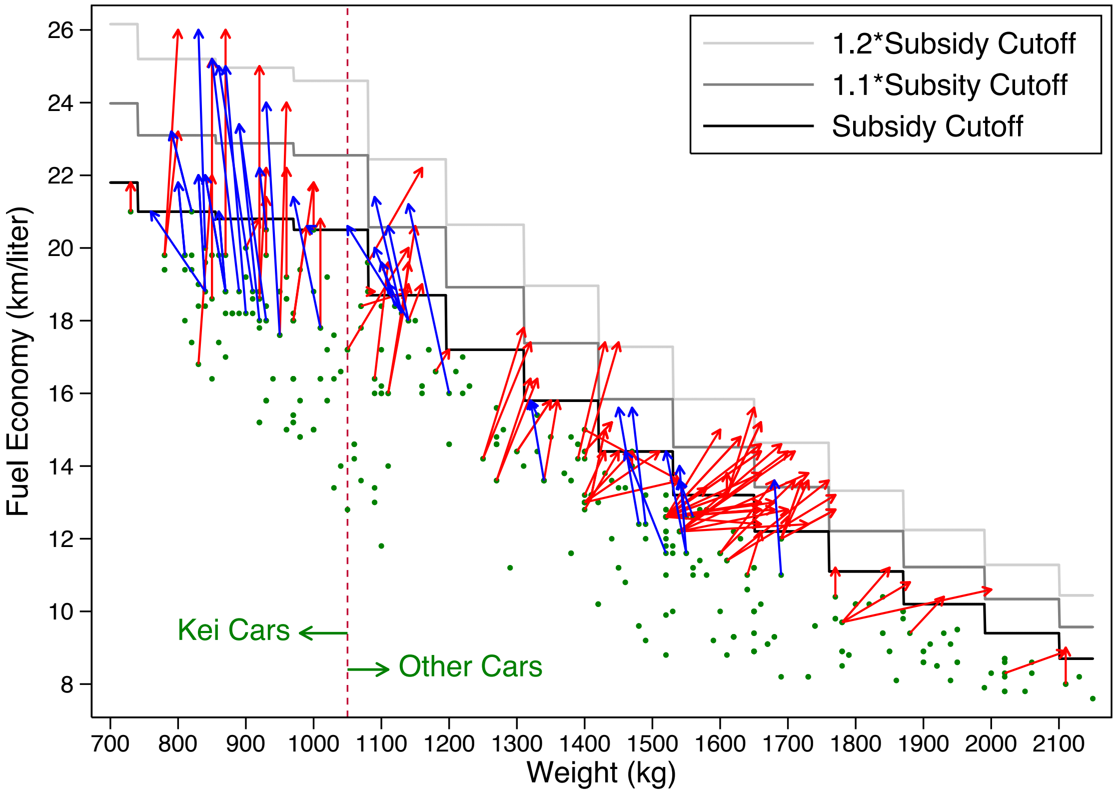
Appendix Figures

Figure A.1: Net Product Entry



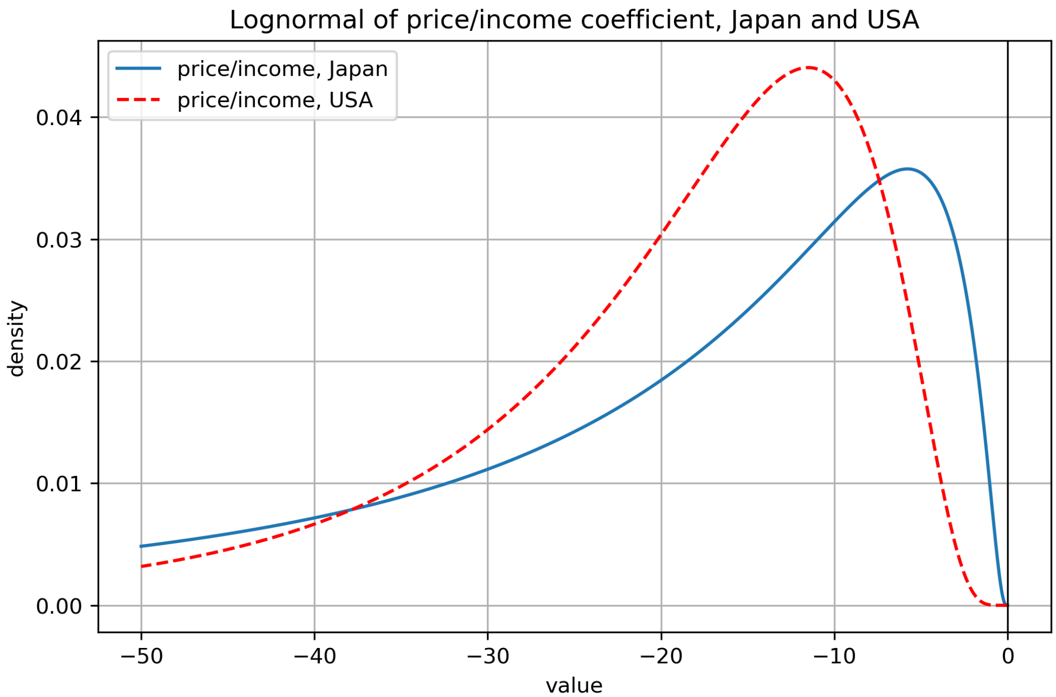
Note: This figure shows the product entry and exit discussed in Section 3.5. For each model-year, we identify product entries and exits to calculate net entry counts, which we then plot separately for the treated and control groups.

Figure A.2: Subsidy take-up



Note: This figure shows the policy induced variation. We construct panel data of car models by linking cars sold in 2008 (before the policy change) and 2012 (three years after the policy introduction). Each dot in the figure shows a car's starting values of fuel economy and weight in 2008. For the cars that qualified for the new subsidy in 2012, we also show vectors connecting each car's starting position in 2008 to its final position in 2012.

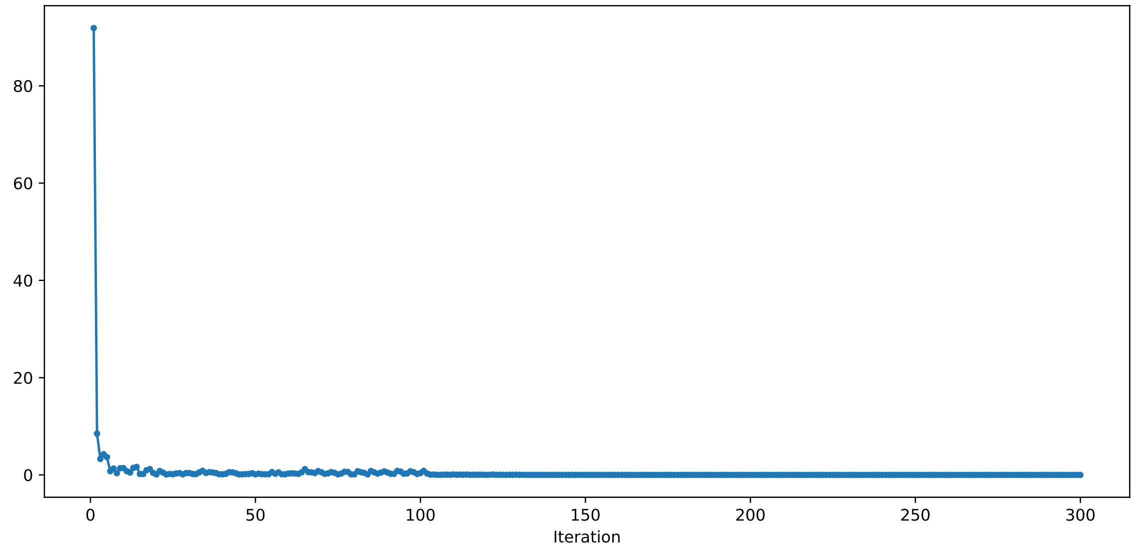
Figure A.3: Log-Normal Distribution of Price/Income Coefficients



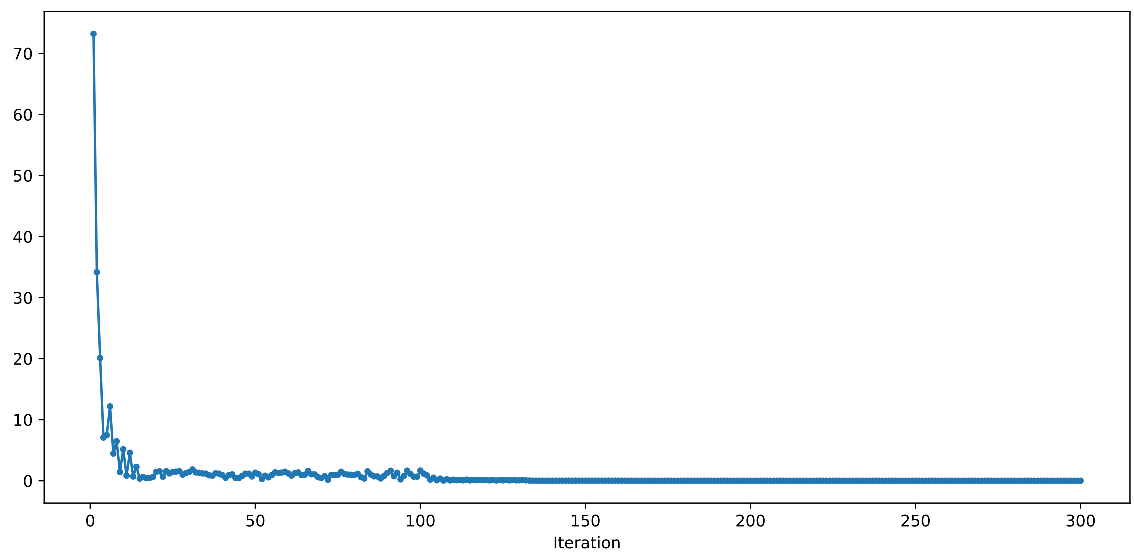
Note: This figure shows the distributions of price coefficients estimated by the random-coefficient logit model in Section 5.1.

Figure A.4: Convergence of the Iterative Procedure

Panel A: Japan (the vertical axis shows % deviation in Equation (7))



Panel B: United States (the vertical axis shows % deviation in Equation (9))



Notes: This figure illustrates the convergence of the iterative procedure described in Section 6.1. At the beginning of the iteration, the left-hand side and right-hand side of Equation (7) in Japan deviate due to the introduction of a counterfactual policy that changes the subsidy in Japan. This policy change also induces a deviation from Equation (7) in the U.S. The figure shows that after approximately 100 iterations, the median value of these deviations converges to zero, yielding a new counterfactual equilibrium.

Appendix Tables

Table A.1: Baseline Characteristics of Treatment and Control Groups Prior to the Subsidy

	Treated		Control		Difference		Adjusted Difference	
	Mean	S.D.	Mean	S.D.	Mean	S.E.	Mean	S.E.
Price (1,000 USD)	24.1	(7.8)	28.1	(7.7)	-4.0	(2.0)	-0.7	(1.9)
Miles per gallon	25.7	(5.5)	18.9	(3.8)	6.8	(1.3)	1.4	(1.1)
Horsepower	187.2	(57.0)	237.3	(55.3)	-50.0	(15.5)	-13.6	(13.1)
Length (feet)	15.3	(0.7)	16.6	(1.5)	-1.4	(0.4)	-0.2	(0.2)
Width (feet)	5.9	(0.2)	6.3	(0.3)	-0.4	(0.1)	-0.1	(0.1)
Height (feet)	5.1	(0.4)	5.8	(0.4)	-0.7	(0.1)	-0.1	(0.1)
Wheelbase (feet)	8.9	(0.4)	10.0	(1.3)	-1.1	(0.3)	-0.1	(0.1)
Footprint (square feet)	52.6	(3.6)	62.7	(10.1)	-10.1	(2.7)	-1.5	(1.2)
Weight (1,000 lbs)	3.3	(0.5)	4.2	(0.8)	-0.9	(0.2)	-0.2	(0.2)

Notes: This table reports summary statistics of vehicle characteristics in 2008, one year prior to the introduction of the Japanese fuel economy subsidy, for Japanese vehicles sold in the U.S. market. The treated group consists of models sold in both the U.S. and Japan, while the control group includes models sold in the U.S. but not in Japan. S.D. denotes the standard deviation, S.E. refers to the standard error of the difference in means. The "difference" column reports unadjusted differences in means. The "adjusted difference" column reports differences in means controlling for body-type fixed effects and therefore absorbs variation across body types. All statistics are weighted by sales volumes.

Table A.2: American Automakers: Spillover Effects of Japan's Fuel-Economy Subsidy on the US Market

Dependent variable: Log fuel economy of American vehicles in the U.S. market

	(1)	(2)	(3)
Treated × Post	-0.027	-0.025	-0.068
	(0.030)	(0.028)	(0.029)
N	21,567	21,567	21,567
Model FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Year FE × Truck FE	No	Yes	Yes
Year FE × Firm FE	No	No	Yes

Note: This table shows the OLS regression results of equation (1). The dependent variable is the log of fuel economy (miles per gallon) at the make-model-trim level between model years 2003 and 2019. During this period, 94 unique models were sold in both markets, while 42 unique models were sold in the United States but not in Japan. All regressions are weighted by the average annual sales. Standard errors are clustered at the model level. The data include all vehicles sold by American automakers in the US automobile market.

Table A.3: Robustness Analysis Using Triple-Difference Estimation (with Further Granular Fixed Effects)

Dependent Variable: Log Fuel Economy

	(1)	(2)	(3)	(4)
Treated × Post × Japanese Automakers	0.138	0.141	0.142	0.119
	(0.041)	(0.040)	(0.040)	(0.032)
Observations	30,665	30,665	30,665	29,235
Model FE	Yes	Yes	Yes	Yes
Year FE × Treated FE	Yes	Yes	Yes	Yes
Year FE × Treated FE × Truck FE	Yes	Yes	Yes	Yes
Year FE × Firm FE	Yes	Yes	Yes	Yes
Year FE × Treated FE × Higher-weight FE	Yes	No	Yes	Yes
Year FE × Treated FE × Higher-wheelbase FE	No	Yes	Yes	Yes
Year FE × Treated FE × Body-style FE	No	No	No	Yes

Note: This table presents the triple-difference estimation results described in Section 3.2 with further granular fixed effects. The dependent variable is the log of fuel economy (miles per gallon) at the make-model-trim level between model years 2003 and 2019. All regressions are weighted by the average annual sales. Standard errors are clustered at the model level. The data include all vehicles sold by Japanese automakers (Honda, Isuzu, Lexus, Mazda, Mitsubishi, Nissan, Subaru, Suzuki, and Toyota) and those sold by American automakers in the US automobile market (Buick, Cadillac, Chevrolet, Chrysler, Dodge, Fisker, Ford, GMC, Hummer, Jeep, Lincoln, Mercury, Oldsmobile, Pontiac, Saturn, Tesla, and Wheego).

Table A.4: Potential Spillover Effects on Other Product Attributes

Dependent variable is the log of each vehicle characteristic in the US market.

	(1) MPG	(2) Horsepower	(3) Price	(4) Wheelbase	(5) Footprint	(6) Weight
Treated × Post	0.083	-0.062	0.001	-0.010	-0.001	-0.006
	(0.026)	(0.045)	(0.019)	(0.007)	(0.008)	(0.016)
N	9,098	9,134	9,124	9,134	9,134	9,120

Note: This table shows the OLS regression results of equation (1). The dependent variable is the log of each car attribute at the make-model-trim level between model years 2003 and 2019. All regressions are weighted by the average annual sales. Standard errors are clustered at the model level. Panel A includes vehicles sold by Japanese automakers (Honda, Isuzu, Lexus, Mazda, Mitsubishi, Nissan, Subaru, Suzuki, and Toyota). Panel B includes vehicles sold by American automakers (Buick, Cadillac, Chevrolet, Chrysler, Dodge, Fisker, Ford, GMC, Hummer, Jeep, Lincoln, Mercury, Oldsmobile, Pontiac, Saturn, Tesla, and Wheego). Year by Car or Truck FE, Model FE, and Year by Make FE

Table A.5: Difference-in-differences Estimation on Entry, Exit, Net Entry

	(1) Entry Ratio	(2) Exit Ratio	(3) Net Entry Ratio
Treated × Post	0.063	0.038	0.010
	(0.054)	(0.056)	(0.064)
N	32	32	30
Year FE	Yes	Yes	Yes
T-C group FE	Yes	Yes	Yes

Note: For each model-year, we identify product entries and exits to calculate net entry counts. We then compute the entry, exit, and net entry ratios for each group by dividing the respective counts of entry, exit, and net entry by the total number of models in that group for the given year.

Table A.6: Additional Evidence from Other Countries: Global Spillover Effects on Fuel Economy

Panel A: Germany

	(1)	(2)	(3)	(4)
Treated × Post	0.103	0.092	0.078	0.076
	(0.034)	(0.028)	(0.024)	(0.020)
Treated	-0.263	-0.263		
	(0.114)	(0.115)		
Post	0.044		0.047	
	(0.021)		(0.014)	
N	547	547	543	543
Year FE	No	Yes	No	Yes
Model FE	No	No	Yes	Yes

Panel B: India

	(1)	(2)	(3)	(4)
Treated × Post	0.173	0.144	0.285	0.272
	(0.135)	(0.142)	(0.056)	(0.060)
Treated	-0.016	-0.016		
	(0.139)	(0.143)		
Post	0.115		-0.006	
	(0.123)		(0.009)	
N	147	147	145	145
Year FE	No	Yes	No	Yes
Model FE	No	No	Yes	Yes

Note: These tables shows our DID estimation in Equation (1) using data from Germany and India.