

Externality of Driving Luxury Vehicles and Optimal Taxation

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Abstract

Under tort law, where the at-fault driver is responsible for the repair costs of another party, driving a luxury vehicle with higher repair costs creates a negative externality. A Pigouvian tax on luxury vehicles, or a vehicle-value-based premium, can internalize this externality. Using novel micro-level automobile sales and repair cost data, and exploiting the introduction of a luxury vehicle tax in British Columbia, we find that for each dollar in vehicle cost, there is an externality of \$0.10. Additionally, the luxury vehicle tax shifts people to buy less expensive cars with lower repair costs. We estimate a structural model to show that the optimal tax would increase welfare by 0.8% of the British Columbia automobile industry, extrapolating to \$8 billion in the US automobile market.

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1 Introduction

Consider two vehicles that crash as one drives through a red light and the other through a green light. Suppose the vehicle with the green light was a Ferrari, valued at over \$200,000, and the repair cost from the accident is \$100,000. Under tort law, the driver at fault is responsible for the damage from the accident. Therefore, the driver at fault is responsible for the \$100,000 repair cost, which the insurance company covering the liability insurance will reimburse.

Now consider another scenario, where everything else is the same except that the driver with the green light was driving a Civic, whose repair cost was only \$20,000. In this case, the insurance company of the at-fault driver would only need to pay \$20,000 for the repair cost. Driving a Ferrari instead of a Civic creates a negative externality, as the insurance company of the at-fault driver needs to pay additional repair costs.

Economic theory suggests that allocation inefficiency could arise if consuming certain goods leads to externalities. A social planner can achieve the socially optimal level of consumption by making consumers internalize the externalities they create. In the context of luxury vehicles, this can be achieved through taxing the purchase of luxury vehicles or charging higher premiums for automobile liability insurance. If such corrective taxation leads to a significant decrease in the purchase of luxury cars, it implies that the size of the efficiency gain is large.

This paper studies the economics of the externality of driving luxury cars and quantifies the welfare implications of taxing luxury vehicles. Luxury vehicles constitute a significant portion of automobile sales (e.g., 20% in the U.S.), and the repair costs of these vehicles are substantially higher than those of economy cars. For instance, in Korea, imported vehicles—considered luxury vehicles in Korea—account

for 33% of the total repair costs. However, the total premiums paid by imported vehicle owners for liability insurance only account for 15% of the total premiums. This is because the premium for liability insurance is essentially the same regardless of the car’s value, due to tort law mandating that the vehicle’s repair cost be paid by the at-fault party. Therefore, the current liability insurance system creates the externality of driving luxury vehicles.

For countries experiencing a rapid increase in luxury vehicle ownership, this distortion has been noticed by the government, as it creates allocation inefficiency and adverse distributional effects, with the choice of luxury vehicles by wealthy drivers increasing the premiums of lower-income drivers. British Columbia, Canada, has pioneered efforts to correct this distortion, which serves as the empirical setting for our study. As British Columbia runs a province-owned automobile insurance system, it recognized the issue and adopted a policy in 2016 where the insurer charges higher premiums for luxury vehicles. Additionally, in 2018, British Columbia adopted a luxury vehicle tax, where cars priced over \$125,000 Canadian dollars (CAD) had their sales tax increase from 10% to 15–20%.

We exploit this tax policy variation in a difference-in-difference setting by comparing model-level automobile sales before and after the luxury vehicle tax was adopted in British Columbia versus Quebec. We use novel model-level automobile sales transaction data obtained from the records of a firm that provides a platform to facilitate automobile purchasing. Given the nonlinear nature of the tax policy, which affected only a small share of high-end cars near or above the tax threshold, a standard difference-in-differences approach may not fully capture the policy’s impact. Therefore, we use the nonlinear difference-in-differences estimation method suggested by Athey and Imbens (2006) to estimate the tax’s effect on every quantile of automobile sales (not just on the mean). Using this econometric framework, we find that the

luxury vehicle tax reduces the sales of luxury vehicles.

Next, we build a model of vehicle demand and supply to quantify the counterfactual optimal policy, requiring drivers of expensive cars to fully internalize the associated additional repair costs. The model requires two key parameters: how much a more expensive car increases the repair cost of the insurer, and how taxing a more expensive car will shift consumers toward cheaper cars. We use model-level repair cost data inferred from U.S. collision insurance data to estimate the first parameter, and we estimate the second parameter using a structural model combined with quasi-experimental tax change variation. Our findings suggest that the gain from the optimal policy gain is 0.8% of the car’s price. Considering that the US automobile industry is valued at \$1 trillion US dollars (USD) yearly, our findings suggest that the policy can improve the US automobile market’s allocation efficiency by \$8 billion USD.

Our paper contributes to the literature studying the externalities of driving. Vickrey (1968) was the first to conceptualize the idea that driving a car itself creates a repair cost externality under tort law, and Edlin and Karaca-Mandic (2006) estimate the size of this externality by studying how one person’s driving increases other people’s insurance rates. This paper adds to this small body of literature by investigating the externalities associated with driving more expensive vehicles, a topic that is recently discussed in policy circles in many countries as they consider policy changes. Moreover, to our knowledge, this is the first paper to quantify the allocation inefficiency arising from these accidental externalities. To achieve this, as illustrated by our toy example, estimating the size of the externality that previous papers focused on is not sufficient, as it is necessary to understand individuals’ willingness to pay for the externalities they create. We present a credible identification strategy with novel data to estimate the demand for vehicles, enabling our paper to provide the efficiency

gains of optimal taxation.

In Section 2, we motivate our research through a simple toy model that delivers the intuition for empirically quantifying the welfare gain of optimal taxation. Section 3 describes the data and the institutional details of our identification strategy. Section 4 explains our empirical method and provide design-based results on how taxing luxury vehicles affects purchase patterns. In Section 5, we build an empirical structural model based our results from an econometric method by Athey and Imbens (2006) and quantify the welfare gain of optimal taxation. Section 6 concludes.

2 Toy model as a motivation

The goal of this section is to use a toy model to explain the economic logic behind the optimal taxation of luxury vehicles and to motivate our research design and data for empirical investigations.

Demand Suppose there are two types of cars: luxury vehicles priced at \$200,000 (henceforth Canadian dollars, unless specified otherwise) and economic vehicles priced at \$20,000. Everyone must choose between these two cars. While everyone values the economic vehicle at the same amount of \$20,000, they value the luxury vehicle differently. Individuals' willingness to pay (WTP) for a luxury vehicle is denoted by α , where α follows the distribution $F(\alpha)$. Therefore, the shape of $F(\alpha)$ will determine the demand for luxury vehicles.

Externality For each driver, there is a probability p that she will crash the other car. When a car accident occurs, the insurance company of the at-fault driver must fully pay for the repair cost of the other party.

Suppose the repair cost of the vehicle is proportional to the car price, i.e.,

$$\text{Repair Cost} = a \times \text{Car Price}$$

Therefore, when a driver chooses a luxury vehicle over an economic car, the externality cost is

$$\text{Externality} = p \times a \times (\$200,000 - \$20,000) = p \times a \times \$180,000$$

Equilibrium without tax Suppose there is no tax on luxury vehicles. People whose WTP α is greater than the private cost—the market price of the luxury vehicle \$200,000—will purchase the luxury vehicle, while others will buy economic cars.

However, whenever a luxury vehicle is purchased, there is an additional cost that society must bear, which is $p \times a \times \$180,000$. The socially optimal outcome occurs when an individual's WTP is greater than the social cost, which is the sum of the private cost and the externality: $\$200,000 + p \times a \times \$180,000$. The deadweight loss (compared to the socially optimal outcome) in a market without a tax is represented by the triangle in Figure 1.

Pigouvian taxation and the size of efficiency gain A simple Pigouvian taxation that taxes luxury cars for their externality will be an optimal taxation policy. This policy achieves the socially optimal quantity, and the efficiency gain is represented by the deadweight loss triangle. The size of this efficiency gain is an empirical question that our paper aims to answer and is determined by two sufficient statistics:

- *The Size of the Externality:* The size of the externality determines the height of the deadweight loss (DWL) triangle. The greater the average repair cost gener-

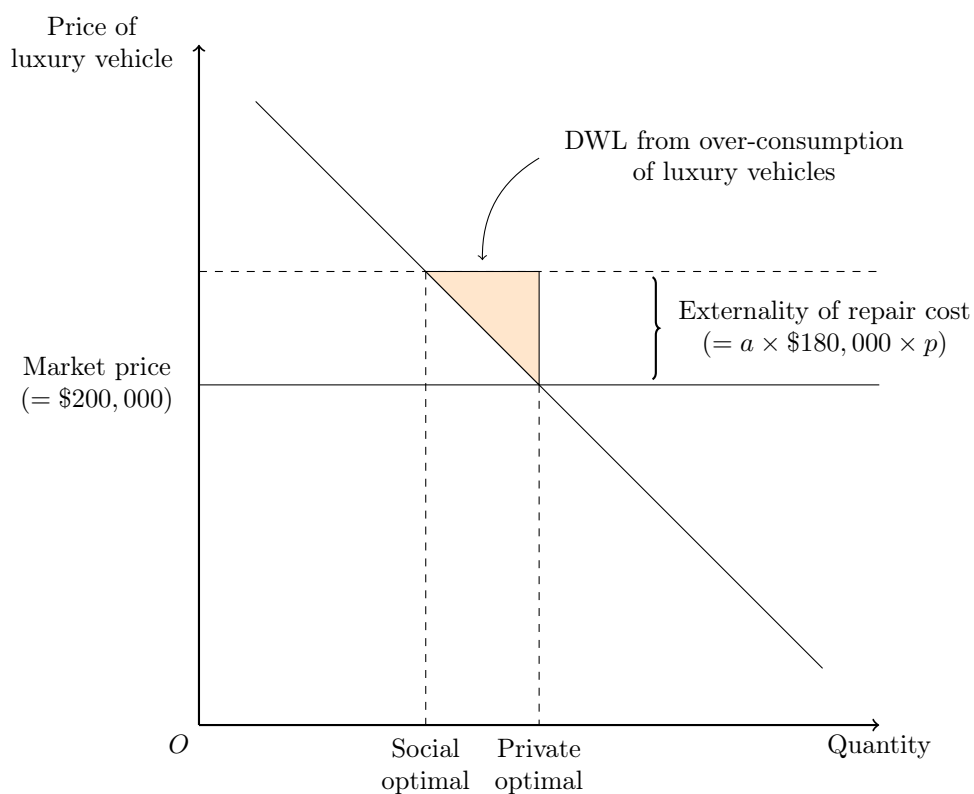


Figure 1: Deadweight loss without tax

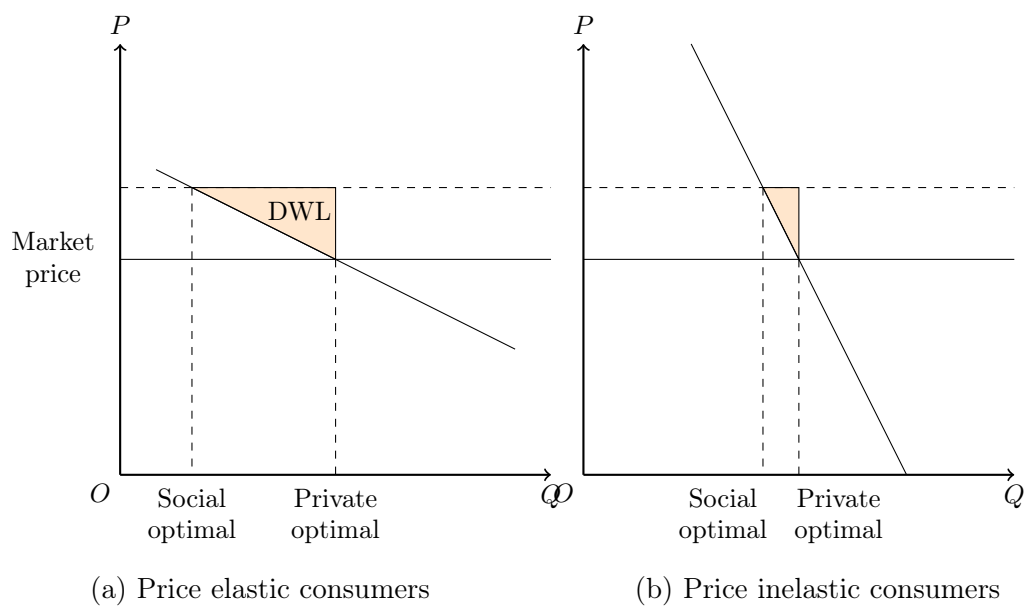


Figure 2: Size of efficiency gain and price sensitiveness

ated by luxury vehicles compared to economic cars, the larger the externality.

- *The Slope of the Demand Curve:* The slope of the demand curve determines the width of the DWL triangle, as illustrated in Figure 2 . If consumers of luxury vehicles are highly price-sensitive, the efficiency gain would be high because it implies that many individuals' WTP for the car is not sufficiently large to cover the externality they generate. On the other hand, if demand is price inelastic, most people are willing to pay well above the social cost, so the efficiency gain from taxation would be minimal, and the tax would primarily serve as a wealth redistribution instrument.

This toy example illustrates the importance of two data sources to quantify the efficiency gain of optimal taxation:

- Data source that provides information on the demand for luxury vehicles that can credibly estimate consumers' price sensitivity
- Data source that informs how much higher the repair costs of luxury vehicles are (the parameter a in a toy model)

The next section illustrates our data and institutional setting to credibly estimate relevant parameters.

3 Data and institutional detail

Automobile sales data We use proprietary automobile sales data consisting of model-level sales information in Canada for transactions completed through auto financing. The data company provides a platform for automobile dealers and manufacturers to facilitate automobile financing, and the transactions that occur through its platform are captured in the data they provided to us, which include two data.

Application Data and Transaction Data The application data contains data on consumers’ applications for auto-financing for their planned purchases. The data includes the application date, automobile make and model year, whether the car is used or new, manufacturer’s suggested retail price (MSRP) for new cars, fair value for used cars, the cash equivalent price of the car, and the total amount financed. The transaction file is a subset of the application records and includes only the transactions that were approved and finalized. We use the transaction data to capture actual demand, as it includes only completed transactions. In contrast, we use the application data to extract each model’s price information more comprehensively, as it includes prices for cars even when the transaction did not ultimately go through.

We now introduce each variable in the dataset.

Cash Equivalent Price Since the data is collected through a platform for auto-financing, only transactions involving auto-financing are tracked. If automobiles are purchased with 100% cash, such transactions are not captured. The data includes two variables related to how much consumers paid for their purchases: “Total Amount Financed” and “Cash Equivalent Price.” The total amount financed reflects how much the consumer actually paid using financing, while the cash equivalent price represents what the consumer would have paid if they had paid 100% in cash. This cash equivalent price is recorded by the dealer when they submit the auto-finance deal. Although the consumer didn’t pay 100% in cash for each deal, we use the cash equivalent price rather than the total amount financed to infer the consumer’s total payment. This is because the total amount financed does not capture any down payment made by the consumer or trade-in value, while the cash equivalent price does not have such limitations.

MSRP and Fair Value Price: The MSRP is the price that the manufacturer

recommends a retailer charge for a product. MSRP serves as a reference point for consumers, though the actual sale price can be higher or lower depending on various factors such as dealer pricing, negotiations, incentives, and market conditions. One important distinction between MSRP and the cash equivalent price is that MSRP is set at a national level and does not vary by province or dealer. Therefore, MSRP can be used as a nationwide proxy for the quality (or the degree of luxury) of a car.

Model and Make: The data tracks the automobile make, model, and model year. This information will be used alongside MSRP to construct a measure of the automobile’s quality. However, for dealers and manufacturers that do not use the platform, such transactions are not captured in our data.

The data only cover automobile brands that use the data company’s service, and only transactions that are financed—if the transaction was paid 100% in cash, it will not be in their system. This raises concerns about the representativeness of our data. We have obtained population-level, model-level registration data for British Columbia and Quebec to adjust for representativeness, although such adjustments remain to be done for now.

Highway Loss Data Institute (HLDI) report To measure how much luxury vehicles create additional repair cost externalities compared to cheaper cars, we use data from the Highway Loss Data Institute, which is publicly available and measures each car model’s average loss for collision insurance. The data include each automobile’s model level average loss, frequency of accident (of the at-fault driver) and the loss conditional on the accident. Collision insurance covers the repair cost for the policyholder’s own car when they are at fault. Therefore, the more expensive the policyholder’s car, the higher the loss should be for the insurer. As a result, insurers

adjust the premium based on this loss.

Because we are focusing on the externality associated with liability insurance (i.e., how much owning an expensive car causes loss to the other party for repair costs), the ideal data would be liability insurance data detailing how much the at-fault driver’s insurer paid for the innocent driver’s repair costs. We are unable to find such data. Nevertheless, the collision insurance data provide a benchmark for how much more repair costs luxury vehicles generate compared to cheaper cars. In Section 5.5, we discuss how we use the data from collision insurance to infer relevant information for the liability insurance system.

4 Institutional detail

In April 2018, British Columbia introduced a luxury vehicle tax. Prior to the reform, a 10% provincial sales tax was imposed on all vehicles. However, starting in April 2018, for cars priced above \$125,000, the *average* tax rate increased to 15%, and for cars priced above \$150,000, it increased to 20%. This policy not only creates a strong incentive to substitute toward a cheaper car, but it also introduces a discontinuous incentive at the \$125,000 and \$150,000 price points. The marginal price change from \$124,900 to \$125,000 and from \$149,900 to \$150,000 can result in a significant difference in the after-tax price, by as much as \$6,250 and \$7,500, respectively. Figure 3 illustrates how the tax reform affects the total tax amount paid by customers. We exploit British Columbia’s policy reform in the spirit of a difference-in-differences approach by comparing the change in automobile sales demand in British Columbia (BC; the treatment group, which underwent the tax reform) to that in Quebec (QC; the control group, which did not experience a tax reform).

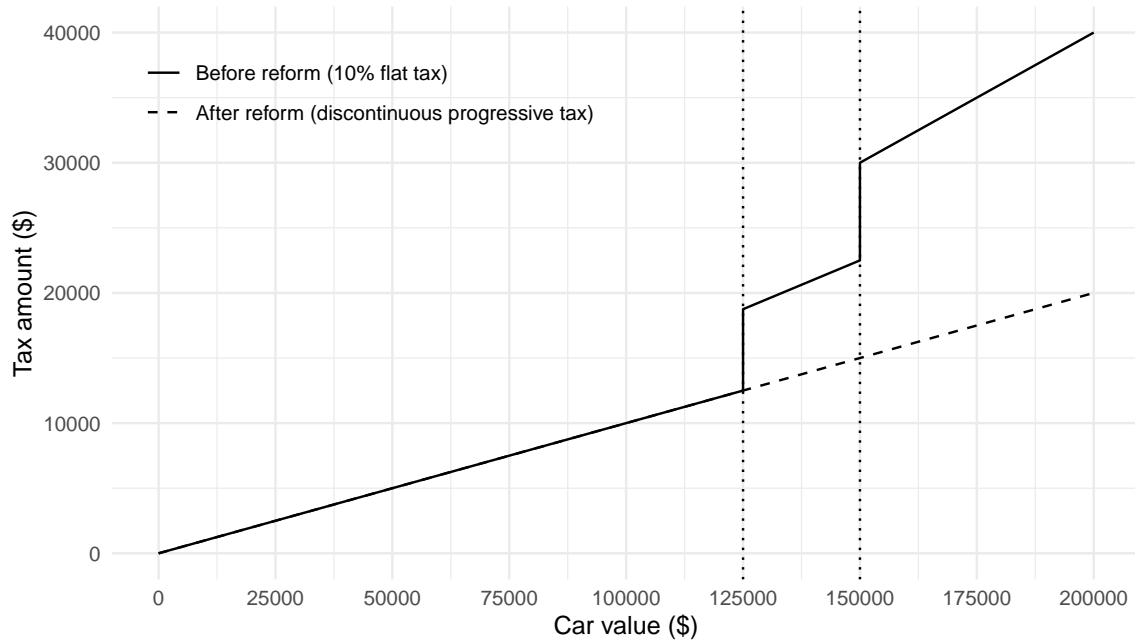


Figure 3: vehicle sales tax change in British Columbia

5 Reduced form analysis

5.1 Econometric framework

The goal of this section is to investigate how the luxury vehicle tax implemented in 2018 affected automobile demand. The greater the extent to which the luxury sales tax shifted demand toward cheaper cars, the more efficiency gains could be realized from a carefully designed luxury sales tax that internalizes the externality of repair costs.

The empirical challenge in our setting arises from the fact that the luxury sales tax introduced in BC in 2018 is highly nonlinear, affecting only a small portion of cars. As discussed in the previous section, before the reform, the sales tax was 10% for all vehicles. However, after the reform, the *average* sales tax for vehicles became 15% once the sales price exceeded \$125,000, and 20% once it exceeded \$150,000. Cars with

sales prices above \$125,000 account for less than 10% of our sales data. As a result, even if there is a meaningful demand shift, it would occur primarily in the segment of very expensive cars, and the effect would be more salient at the tax threshold. Therefore, a simple difference-in-differences approach to assess the causal impact on the *mean* of the treated group (BC) may fail to detect such an effect, potentially masking the effect we want to find.

Therefore, we adopt an econometric framework that helps us analyze the impact of the policy on the *entire distribution* of sales within a generalized difference-in-differences framework, still exploiting BC's reform. We use the method proposed by Athey and Imbens (2006), which allows us to construct the *counterfactual* distribution of automobile demand in the treated group had there been no treatment. This approach is particularly well-suited to our analysis, as the effect is concentrated in specific segments of the automobile demand distribution. We will explain how our setting maps into their econometric framework.

Suppose there is continuous observable scalar θ that measures the automobile quality (with higher values indicating more luxurious vehicles), and we observe the distribution of sales of each quality in both BC and Quebec in each year. Let the density function $f_{s,t}(\theta)$ represent the market share of cars of quality θ among newly purchased in period t and province s , with the corresponding cumulative distribution $F_{s,t}(\theta)$. We let $t = 0$ to refer to the period before BC adopted the new reform, and $t = 1$ to refer to the period after the reform. After attaching quality θ to each car, whose procedure we delineate in Section 5.2, the automobile sales data allow us to observe $F_{BC,0}(\theta)$, $F_{BC,1}(\theta)$, $F_{QC,0}(\theta)$, and $F_{QC,1}(\theta)$.

Note that $F_{BC,1}(\theta)$ is the distribution of sales of θ in BC impacted by the luxury vehicle tax reform. To evaluate the reform's impact on the distribution of θ , we need a *counterfactual* distribution for BC at $t = 1$ in the case without the luxury sales tax

reform, which we denote as $F_{BC,1}^{\text{no reform}}(\theta)$. Since $F_{BC,1}^{\text{no reform}}(\theta)$ is not directly observable, the researcher must construct $F_{BC,1}^{\text{no reform}}(\theta)$ to compare it with the actual data $F_{BC,1}(\theta)$ and assess how the reform affected the distribution of sales of θ .

Athey and Imbens (2006) propose a framework to construct $F_{BC,1}^{\text{no reform}}(\theta)$. The key idea is as follows. Suppose there is a car whose quality is θ^* at $t = 0$. However, at $t = 0$, θ^* was ranked at the top 10% among BC's newly purchased cars, while it was ranked at the top 5% in Quebec. Now, suppose we observe that the top 5% of car qualities purchased in Quebec at $t = 1$ is θ^{**} . Using this information, the top 10% purchased in BC's counterfactual world without treatment (in our setting, BC's tax reform at $t = 1$) will be θ^{**} . The idea is mathematically expressed as:

$$F_{BC,1}^{\text{no reform}}(\theta) = F_{BC,0} \left(F_{QC,0}^{-1} (F_{QC,1}(\theta)) \right) \quad \forall \theta$$

The thought process is as follows. Suppose customer A in BC and customer B in Quebec chose the same quality car, θ^* , at $t = 0$. Athey and Imbens (2006) assumed their choices would again coincide at $t = 1$ (potentially at a quality level different from θ^*) if there was no treatment (i.e., a tax change), which is a distributional analogue of the common trend assumption in standard difference-in-differences analyses. Since customer B in Quebec was in the top 5% of Quebec's new car purchase customers at $t = 0$, what he would have chosen at $t = 1$ would align with what Quebec's top 5% of new car purchase customers choose at $t = 1$, which is θ^{**} . Therefore, customer A in BC will choose θ^{**} at $t = 1$, and that will correspond to what the top 10% of BC's new car purchase customers would have bought when there was no tax change.

5.2 Construction of quality measure

The previous discussion suggests we need data on the quality θ of cars. This measure needs to satisfy two conditions:

- It should capture how luxurious or high-quality a car is.
- The measure should be *invariant* to the tax policy we are studying.

While the automobile pre-tax price is the most natural measure of quality for the first reason, it cannot be used as the quality measure for the second reason: the tax policy can directly affect the price of the car through pass-through. For example, suppose that after a luxury vehicle sales tax is introduced, every car's price decreases by 10% as a result of pass-through, but everyone's car choice remains the same as before. In this case, the policy did not actually change automobile demand and, therefore, did not correct any repair cost externality. However, if we use the pre-tax price as a measure, this would mislead us into thinking that the policy made customers buy less luxurious cars and reduced the externality.

To construct a quality measure that is highly associated with prices but invariant to the tax change, we create a *predicted price* as a quality measure. The idea is to use the model-level information we have and develop a prediction model that estimates the actual car sales price. While fitting the prediction model, we exclude data from BC *after* the tax reform to ensure that the prediction is invariant to the tax policy change.

The following regression models are used to predict the pre-tax price.

- For a transaction i of a new car:

$$\begin{aligned}
CashPrice_i = & \beta_0 + \beta_1 \cdot MSRP_i + \sum_y \beta_{2y} \cdot Year_i^y + \sum_m \beta_{3m} \cdot Month_i^m \\
& + \beta_4 \cdot BC_i + \sum_y \beta_{5y} \cdot (MSRP_i \times Year_i^y) \\
& + \sum_m \beta_{6m} \cdot (MSRP_i \times Month_i^m) \\
& + \beta_7 \cdot (MSRP_i \times BC_i) + \sum_b \beta_{8b} \cdot Make_i^b \\
& + \beta_9 \cdot Age_i + \sum_b \beta_{10b} \cdot (Make_i^b \times Age_i) + e_i
\end{aligned}$$

where $Year_i^y$ is a binary variable that takes value 1 if the transaction year is $y \in \{2016, 2017, \dots, 2020\}$, and similarly for $Month_i^m$. $Make_i^b$ is a binary variable that takes value 1 if the make of the transacted car is $b \in \{Acura, Alfa Romeo, \dots, Volvo\}$.¹ Age_i is the difference between the transaction year of i the year the care being transacted is produced.

- The same regression model (with different coefficient estimates) applies to used car transactions, with the only difference that $UsedValue_i$ replaces $MSRP_i$:

$$CashPrice_i = \beta_0 + \beta_1 \cdot UsedValue_i + \sum_y \beta_{2y} \cdot Year_i^y + \dots$$

The predicted price of the same car may differ due to provincial effects and time effects. Certain characteristics, such as MSRP, are allowed to be interacted with province, meaning that an additional increase in MSRP may be valued differently across provinces. Figure 4 shows the relationship between the predicted price and

¹This is an example for explanatory purposes and does not mean these makes are actually included in our data.

the actual price for both new and used cars, pooled across provinces and periods *excluding* British Columbia at $t = 1$. As expected, the predicted price–actual price pairs are distributed around the 45 degree line (the dashed line).

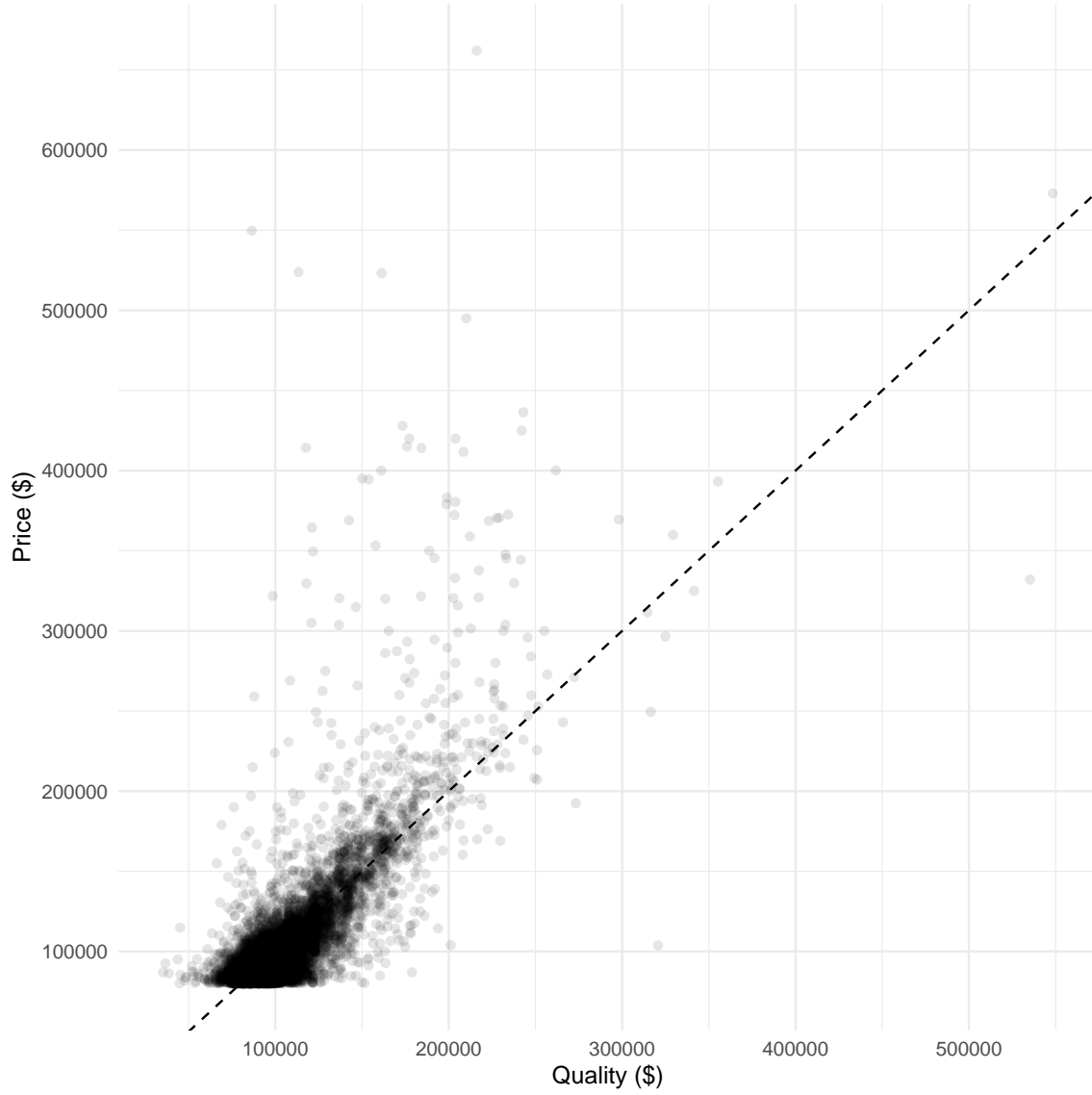


Figure 4: The relationship between predicted pre-tax price and actual pre-tax price

5.3 Causal impact of tax on quality choice

We now apply the estimation method by Athey and Imbens (2006) and generate $F_{BC,1}^{\text{no reform}}(\theta)$. We overlay it (which we call the *no reform* distribution) with $F(\theta)_{BC,1}$ (which we call the *actual* distribution under the tax reform) in Figure 5. Comparing these two distributions allows us to causally examine how a tax reform shifts automobile demand. The null hypothesis that the two distributions are the same is strongly rejected by a test suggested by Athey and Imbens (2002) with p -value 0.000.²

The results suggest that the distribution in the world without the tax reform first-order stochastically dominates the distribution in the world with the tax reform. This suggests that the introduction of the tax shifts car choices toward lower-quality (less luxurious) vehicles.

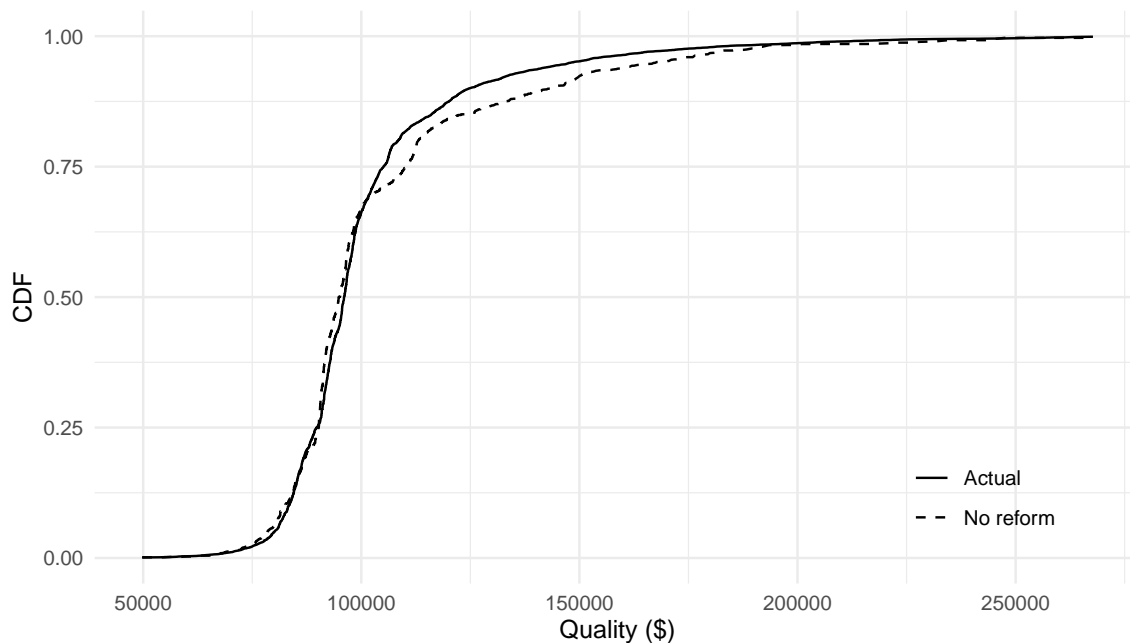


Figure 5: The distribution of quality θ in two regimes

²We conducted the test with nine deciles, resulting in the test statistic of value 129.86 which would follow $\chi^2(9)$ under the null hypothesis.

5.4 Other empirical results guiding our structural modeling choice

Here, we introduce one empirical fact that will be important for us to incorporate in our structural model estimation.

Bunching of prices but not of qualities We find that while customers respond strongly to the tax change, resulting in significant bunching at the cutoff tax point for pre-tax prices. However, there is no similar bunching in the quality (which is a predicted pre-tax price) level. Figure 6 illustrates this. One explanation is that customers may face different prices for the same quality car. This is common in automobile transactions, as prices are often determined by the bargaining between the customer and the dealer. To illustrate, suppose customer A and customer B both want to buy luxury vehicles and aim to avoid additional sales tax by spending just below the tax cutoff point. If customer A negotiates a better deal with the dealer than customer B due to greater bargaining power, customer A may end up purchasing a higher-quality car than B for the same price. We will incorporate this heterogeneity in bargaining into our structural estimation to better fit the data.

5.5 The relationship between the car quality and the repair cost externality

Insurance Report from HLDI provides data on collision losses for various vehicle models from the collision insurance system, specifically detailing how much an at-fault driver's insurance companies pay for the repair costs of the *at-fault* driver's car. Therefore, we first discuss how data from collision insurance can be used to infer information for liability insurance—specifically, how much an at-fault driver's

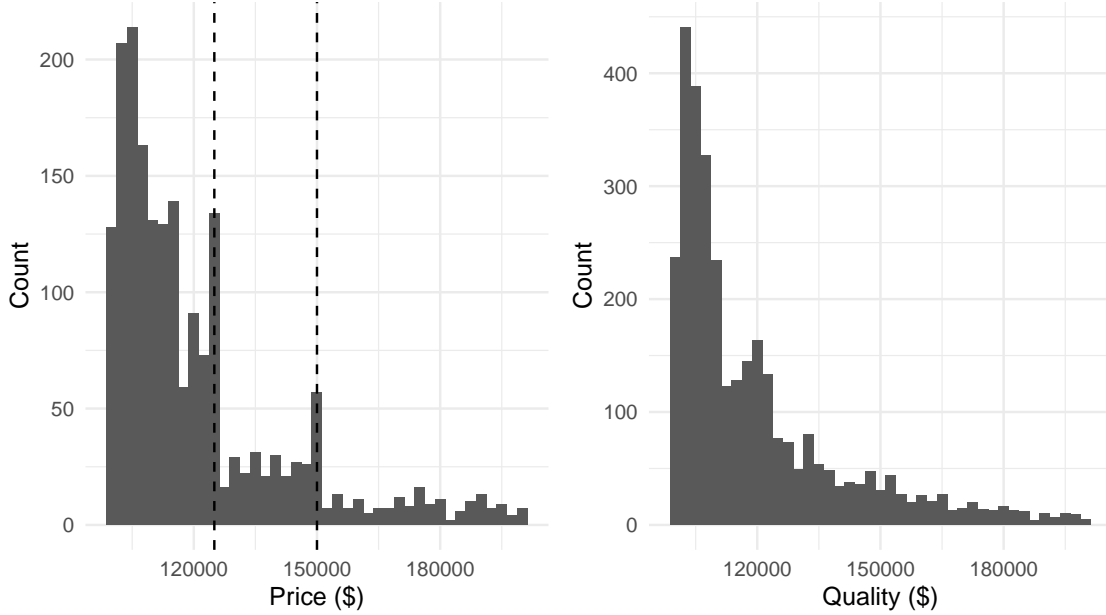


Figure 6: Bunching of pre-tax prices at the two thresholds, but not of qualities (predicted pre-tax prices)

insurance companies pay for the repair costs of the *innocent* driver's car.

Suppose the probability of an accident caused by the at-fault driver i is homogeneous across drivers, which is p^3 . Suppose that for each accident, conditioned on the accident, the repair cost for the innocent driver's car, which has quality θ , is $\beta\theta$, and the repair cost for the at-fault driver's car, which has quality θ'' , is $\alpha\theta''$. Then, the externality of driving a car that is 1 dollar more expensive in the liability insurance system is βp . Therefore, as long as β is similar to α , and we can get the data of α and p from collision insurance data, using collision insurance data will be reliable for our analysis of liability insurance. In the Appendix A, we show that α and β are very similar based on aggregated statistics obtained from both collision insurance and liability insurance data in Korea, which justifies the use of collision insurance data.

We use HLDI data to regress average annual repair cost (per collision) on vehicle

³This is the probability of the accident over the life cycle of the car.

year and make-model. Figure 7 presents the relationship between the repair cost and car quality θ . Because not all the vehicle year and make-model from the automobile sales data are available from this Insurance Report, we predict the repair cost for all vehicles in the automobile sales data using the fitted coefficients. We then regress the repair cost (severity) on quality, which gives us the incremental repair cost per dollar increase in quality, equaling 0.1354. To arrive at the present value of expected incremental repair cost, we multiply this number by the annual probability of collision⁴ 0.0609 and by the average years of car usage 12.1.⁵ The expected incremental repair cost per dollar is calculated as 0.0997.⁶ This estimate is similar to the one we derived from Korea’s liability insurance data, which we discuss in more detail in the Appendix A

6 Model of vehicle demand and supply

In this section, we introduce an empirical model of vehicle demand and supply that can be used to quantify the welfare gains of optimal taxation.

6.1 Demand

We consider a model of car demand where consumers exhibit unit demand for cars. The cars are differentiated solely by the uni-dimensional quality measure, denoted as θ . Each consumer i chooses the car that maximizes their payoff, which is the utility net of payment. The payoff from purchasing a car of quality θ is represented by the

⁴This is calculated by dividing the average overall losses by the average claim severity in the 2020–2022 Insurance Report by Highway Loss Data Institute.

⁵According to Bureau of Transportation Statistics, average vehicle years at year 2021 is 12.1. Assuming constant probability of retirement, this equals the expected lifespan of cars.

⁶Removing five outliers—two points with quality exceeding \$400,000 and three points with severity exceeding \$100,000—results in 0.0964, which is not very far from our baseline number.

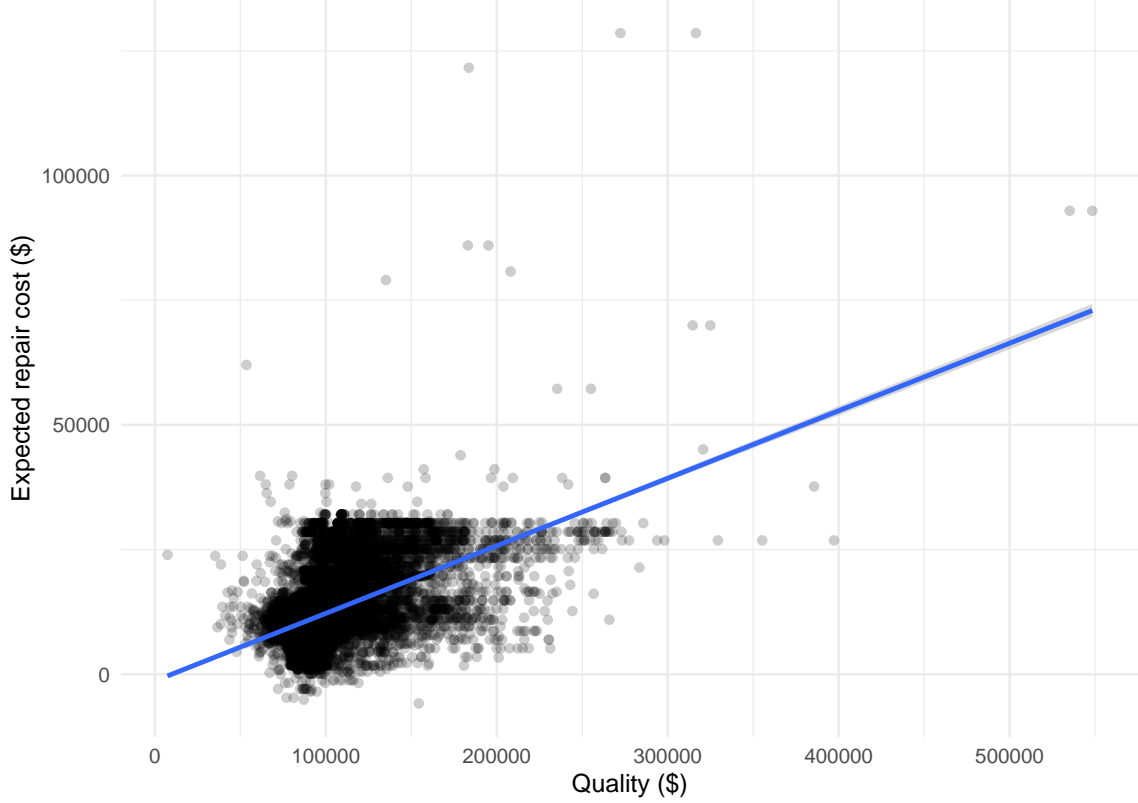


Figure 7: Relationship between quality and repair cost

following payoff function:

$$v_i(\theta, p) = \left(\frac{\alpha_i}{r}\right) \theta^r - (1 + \tau(p(\theta) + e_i)) (p(\theta) + e_i), \quad (1)$$

where α_i represents the consumer's heterogeneous preference towards a higher quality car, e_i represents the consumer's heterogeneous bargaining ability (with lower values indicating higher bargaining power), and r denotes the consumer's elasticity of expenditure on car quality with respect to the price. Let $p(\theta)$ denote the listing price for a car of quality θ set by the dealer— p is a function that maps θ into its listing price. We let $\rho_i(\theta) = p(\theta) + e_i$ indicate the price that a customer i actually faces for a car with quality θ . The term $\tau(\rho)$ captures the tax rate applied to a car sold at price ρ .

Consequently, the total amount paid by the consumer is $(1 + \tau(p(\theta) + e_i))(p(\theta) + e_i)$.

We will denote the consumer i 's choice as

$$\theta_i(p) = \arg \max_{\theta} v_i(\theta, p).$$

We assume that all consumers have the same r , so that consumers are characterized by the pair (α_i, e_i) . Their distribution is specified as follows: $(\alpha_i, e_i) \sim f_{\alpha}(\cdot) \times f_e(\cdot)$. We assume a nonparametric distribution for $f_{\alpha}(\cdot)$, while $f_e(\cdot)$ is parametrized as a normal distribution $N(0, \sigma_e^2)$, with a mean of zero to provide the location normalization.

6.2 Supply

The list price $p(\theta)$ is endogenously set by dealers, potentially leading to pass-through of tax levied on cars. For simplicity, we assume that each quality θ is supplied by a dealer, who specializes in supplying cars of that quality and none others. Each dealer has a constant marginal cost $c(\theta)$ of supplying a car of quality θ . Dealers who provide different qualities compete in the manner of Nash-Bertrand price competition, to maximize their expected profit. Specifically, for quality θ , the listing price $p(\theta)$ is determined by

$$p(\theta) = \arg \max_{p(\theta)} (\mathbb{E}[p(\theta) + e_i | \theta_i(p) = \theta; p] - c(\theta)) q(\theta; p)$$

where $\mathbb{E}[p(\theta) + e_i | \theta_i(p) = \theta; p]$ is the expected payment of a buyer of car with quality θ , when the collection of list prices—not only $p(\theta)$ but also all other dealers' list prices in the market—is given by p . Similarly, the quality $q(\theta; p) \equiv \mathbb{P}[\theta_i(p) = \theta | p]$ depends on all the list prices.

6.3 Identification

All parameters in the demand system are jointly identified. The distribution of α captures the heterogeneity of automobiles, which is identified by the distribution of the quality of cars purchased. Meanwhile, r , a key parameter of interest, governs the price elasticity of automobile quality and is identified by how much the adoption of luxury vehicle tax shifts quality choices. The variance of consumer bargaining power, σ_e^2 , is identified by the degree of price dispersion for the same quality car. The function $p(\theta)$ representing the list price of car quality θ is identified by the observable relationship between quality θ and the transaction price of θ . The extent of tax pass-through is revealed by how much $p(\theta)$ changes in response to the tax.

The supply-side parameters are the marginal costs $c(\theta)$ of cars of quality θ . These are backed out using the firm's first-order conditions from the Nash-Bertrand price competition between dealers, as is standard in the industrial organization literature.

7 Estimation

7.1 Demand estimation

For the estimation of the demand side, we consider two distinct economies, named *actual* and *no reform*, as in the reduced form analysis in Section 5. Both economies represent the economic environment of British Columbia at $t = 1$, but they differ in their tax schemes.

The *actual* economy reflects the reformed tax scheme in British Columbia char-

acterized by the piecewise linear tax structure:

$$\tau(\rho) = \begin{cases} 0.10 & \text{if } \rho < 125,000, \\ 0.15 & \text{if } 125,000 \leq \rho < 150,000, \\ 0.20 & \text{if } \rho \geq 150,000. \end{cases}$$

represented by the graph for *after reform* in Figure 3. In contrast, the *no reform* economy represents the pre-reform tax scheme in British Columbia, which is subject to a uniform linear tax rate $\tau(\rho) = 0.10$ for all ρ (*before reform* in Figure 3).

We permit the pricing schedules of the dealers to vary between the two economies. In the *no reform* economy, the price schedule is $p(\theta) = \theta$, consistent with the fact that θ is constructed to represent the no-reform predicted price in the reduced form analyses (Section 5). In the *actual* economy, we assume that dealers price according to $p(\theta) = k\theta$, where k is a constant reflecting the influence of the reformed tax scheme on pricing behavior.

We estimate the demand parameters $(r, f_\alpha(\cdot), \sigma_e)$ and the pricing schedule parameter (k) using $f_{\text{obs}}^{\text{actual}}(\theta, p)$ and $f_{\text{Athey-Imbens}}^{\text{no reform}}(\theta)$, which represent the observed (actual) joint distribution of quality and pre-tax prices in British Columbia at $t = 1$, and the Athey-Imbens-derived distribution of θ in the no-reform scenario in British Columbia at $t = 1$, respectively.⁷

Our procedure for demand estimation can be understood as a two-step procedure. First, given r , note that there is exactly one $f_\alpha(\cdot)$ that leads to $f_{\text{Athey-Imbens}}^{\text{no reform}}(\theta)$.

⁷Note that we now omit the subscripts $s = BC, t = 1$ that we had in the reduced analysis, as all the distributions in this section pertain to British Columbia at $t = 1$. Instead, we introduce superscripts “actual” and “no reform” to distinguish the (after-reform) nonlinear tax regime and the 10% linear tax regime, and subscripts “obs,” “Athey-Imbens,” and “simulated” to distinguish the observed distribution (directly from the data), the Athey-Imbens-derived distribution (from the reduced form analysis), and simulated distributions we explain momentarily. As such, $f_{\text{Athey-Imbens}}^{\text{no reform}}(\theta)$ here corresponds to $f_{BC,1}^{\text{no reform}}(\theta)$ in Section 5.

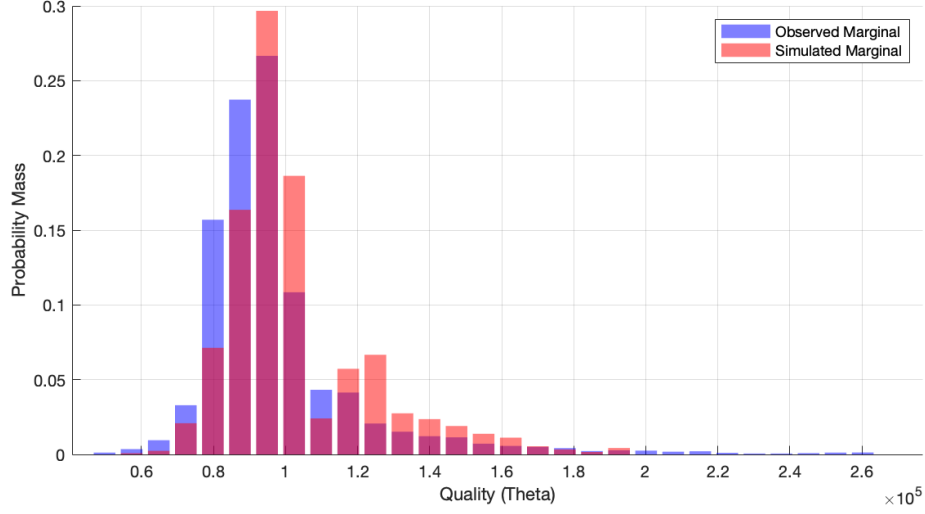


Figure 8: Simulated and observed data in the new tax regime

To see this, note that in the no reform scenario, the optimal choice of θ is a one-to-one function of α_i ; the first-order condition of the consumer's payoff function $v'_i(\theta) = \alpha_i \theta^{r-1} - (1 + 0.10) = 0$ leads to $\theta = (\frac{1.10}{\alpha_i})^{\frac{1}{r-1}}$. We use this to recover $f_\alpha(\cdot)$ nonparametrically given r , which we name $\hat{f}_\alpha(\cdot; r)$.

Secondly, given $\hat{f}_\alpha(\cdot; r)$, we match the joint distribution of quality and pre-tax prices from the actual economy data with the simulated counterpart. Specifically, we minimize the sum of squared residuals between the observed and simulated density functions:

$$\min_{r, \sigma_e, k} \sum_{\theta, p} \left[f_{\text{obs}}^{\text{actual}}(\theta, p) - f_{\text{simulated}}^{\text{actual}}(\theta, p | \hat{f}_\alpha(\cdot; r), \sigma_e, r, k) \right]^2 \quad (2)$$

where $f_{\text{simulated}}^{\text{actual}}$ represents the density function generated by our model for a given set of parameters under the actual regime, i.e., with the tax reform. This procedure gives us our estimates $(\hat{r}, \hat{k}, \hat{\sigma}_e, \hat{f}_\alpha(\cdot; \hat{r}))$.

Figure 8 shows that our model fits well: $f_{\text{obs}}^{\text{actual}}(\theta)$ and $f_{\text{simulated}}^{\text{actual}}(\theta | \hat{f}_\alpha(\cdot; r), \hat{\sigma}_e, \hat{r}, \hat{k})$ align closely. Appendix B gives more details about our demand estimation procedure.

7.2 Supply estimation

Under a linear tax scheme, we have that $\mathbb{E}[e_i|\theta_i(p) = \theta; p] = \mathbb{E}[e_i] = 0$ under our assumption that e_i is independent of α_i . That is, given a price schedule p , the bargaining ability of consumers who choose to buy θ is zero on average, for any θ . This holds because under a linear tax, say $\tau(\rho) = \tau_0$, e_i enters the payoff function (1) additively, thus becoming irrelevant to the optimal choice θ_i .⁸

Using this property, we have a simple first order condition with respect to $p(\theta)$ (for each θ) under a linear tax scheme as:

$$q(\theta; p) + (p(\theta) - c(\theta)) \frac{\partial q(\theta; p)}{\partial p(\theta)} = 0.$$

Under the baseline 10% linear tax as in the counterfactual case of British Columbia, we can further use the quality normalization $p(\theta) = \mathbb{E}[p_i|\theta_i(p) = \theta] = \theta$, to solve for the marginal cost:

$$c(\theta) = \theta + \left[\frac{\partial q(\theta; p \equiv \theta)}{\partial p(\theta)} \right]^{-1} \tilde{q}(\theta)$$

where $\tilde{q}(\theta)$ is the equilibrium quantity.

For estimation, we discretize the support of θ into 15 grid points. Given the estimate of the demand function q and the “observed” (using the Athey-Imbens procedure) distribution of quality in the counterfactual British Columbia $\tilde{q}(\theta)$, we can calculate $c(\theta)$ for each θ on the grid.

⁸Under nonlinear tax schemes, in contrast, $\mathbb{E}[e_i|\theta_i(p) = \theta; p]$ is not zero and depends on p and θ in general.

8 Welfare analysis of optimal taxation

Our analysis using the collision insurance data shows that a one-dollar increase in car price is associated with a \$0.10 (≈ 0.0997) increase in repair cost externality. Therefore, the optimal taxation to correct this bias would be a linear 10%.

Using our structural model, we simulate the equilibrium outcome under this optimal tax and then estimate the consumer surplus, supplier surplus, tax revenue, and externality.

Specifically, given the parameters and a new tax scheme τ , the profit function for quality θ can be written as

$$(p(\theta) + \mathbb{E}[e_i|\theta_i = \theta; p, \tau] - c(\theta))q(\theta; p, \tau),$$

where we emphasize that the demand function q and the expected payment $\mathbb{E}[p(\theta) + e_i|\theta_i = \theta; p]$ depend on the tax scheme τ . Then we have the first order condition with respect to the endogenous list price $p(\theta)$, for each θ of the predefined 15 grid points:

$$\left(1 + \frac{\partial \mathbb{E}[e_i|\theta_i = \theta; p, \tau]}{\partial p(\theta)}\right) q(\theta; p, \tau) + (p(\theta) + \mathbb{E}[e_i|\theta_i = \theta; p, \tau] - c(\theta)) \frac{\partial q(\theta; p, \tau)}{\partial p(\theta)} = 0.$$

We solve (for the 15-dimensional vector p) the system of equations consisting of these 15 first order conditions using a numerical solver. Then we can calculate various surplus components. Specifically, consumer surplus, producer surplus, tax revenue,

and externality due to repair cost are:

$$\begin{aligned}
CS &= \int \max_{\theta} \left[\frac{\alpha_i}{r} \theta^r - (1 + \tau(p(\theta) + e_i))(p(\theta) + e_i) \right] dF(\alpha_i, e_i) \\
PS &= \int (p(\theta_i) + e_i - c(\theta_i)) dF(\alpha_i, e_i) \\
TR &= \int \tau(p(\theta_i) + e_i) dF(\alpha_i, e_i) \\
RC &= \int 0.0997 \times \theta_i dF(\alpha_i, e_i) = 0.0997 \times \mathbb{E}[\theta_i]
\end{aligned}$$

respectively, where $\theta_i = \theta(\alpha_i, e_i)$ is consumer i 's optimal quality choice. Then we compare the total surplus $TS = CS + PS + TR - RC$ resulting from different tax schemes.

Table 1 shows how much each component changes (compared to the no-tax regime) in each counterfactual tax policy scenario. The optimal linear tax of 10% improves the efficiency gain by \$731 CAD per car unit, which is 0.8% of the car's value. Considering that the yearly automobile market size in the United States is \$1 trillion USD, the gain from the optimal taxation is around \$8 billion USD.

Table 1: Differences from No Tax Scenario

Scenario	ΔCS	ΔPS	ΔTR	ΔRC	$\Delta Total$
Linear tax (10%)	-11064.80	+88.32	+10471.55	-1236.13	+731.21
Nonlinear tax (actual)	-12776.19	+37.01	+11145.84	-1772.62	+179.28
Linear tax (15%)	-16188.03	+55.12	+14958.03	-1734.86	+559.98

Notes: CS, PS, TR, RC, and Total denote consumer surplus, producer surplus, tax revenue, repair cost, and total surplus, respectively, in Canadian dollars per car unit. $Total = CS + PS + TR - RC$. All surplus differences are relative to the scenario in which there is no tax.

9 Conclusion

This paper studies the externalities of driving luxury vehicles and their associated efficiency costs. The paper finds that spending an additional dollar on automobile purchases is associated with a 10-cent negative externality in the liability insurance system. Our structural estimation shows that the tax elasticity of expenditure on cars is around 0.24, and these results suggest that the efficiency cost of optimal taxation is 0.8% of the car cost. Extrapolating our result to the U.S. automobile market suggests that this policy could improve efficiency costs by \$8 billion annually in the U.S.

References

- Athey, S. and Imbens, G. W. (2002). Identification and inference in nonlinear difference-in-differences models. Working Paper 280, National Bureau of Economic Research.
- Athey, S. and Imbens, G. W. (2006). Identification and inference in nonlinear difference-in-differences models. *Econometrica*, 74(2):431–497.
- Edlin, A. S. and Karaca-Mandic, P. (2006). The accident externality from driving. *Journal of Political Economy*, 114(5):931–955.
- Vickrey, W. (1968). Automobile accidents, tort law, externalities, and insurance: An economist’s critique. *Law and Contemporary Problems*, 33(3):464–487.

Appendix

A Relationship between repair cost externality and car value

Our welfare calculation relies on our estimate of the relationship between repair cost externalities derived from the HLDI data, which is based on *collision* rather than *liability* insurance data. We were unable to obtain liability insurance data from Canada or the U.S., but we have aggregate statistics on collision insurance and liability insurance from Korea.

Table 2: Insurance Payout Ratios by Vehicle Type

Vehicle Type	Domestic (%)	Imported (%)	Total (%)
Small	73.4	204.7	78.6
Medium	73.5	261.4	100.5
Large	96.9	232.4	133.7
Total	78.4	241.8	101.2

Notes: Insurance Payout Ratio (%) is calculated as $100 \times (\text{Insurance Payout}/\text{Premium})$. Based on personal passenger cars in 2019.

Data: Obtained from the report of the Board of Audit and Inspection of Korea. The table was created by the Insurance Development Institute from insurance data.

Table 3: Share of Each Registered Vehicle Type (2019)

Vehicle Type	Domestic (%)	Imported (%)	Total (%)
Small	35.7	1.4	37.1
Medium	32.7	6.0	38.7
Large	17.8	6.4	24.2
Total	86.2	13.8	100.0

Notes: Based on personal passenger cars in 2019.

Data: Obtained from the report of the Board of Audit and Inspection of Korea. The table was created by the Insurance Development Institute from insurance data.

We first demonstrate that our estimate obtained from the HLDI data is comparable to the figure from Korean liability insurance data. Tables 2 and 3 show that imported vehicles (regarded as luxury vehicles in Korea) account for only 13.8% of the registered vehicles for liability insurance, and their insurance payout ratio is 2.42, while that of domestic vehicles is 0.78. The liability insurance premium during this period is around 220,000 KRW, which allows us to calculate the yearly payout for domestic and imported vehicles. The payout for domestic vehicles was 170,000 KRW, while that of imported vehicles was 525,257 KRW, which is about 3.08 times higher. The average vehicle cost for domestic vehicles sold in 2020 is 33 million KRW, while that of imported vehicles was 68 million KRW. Assuming a vehicle is used for 12 years, we can calculate how much externality is associated with one dollar increase in car expenditure by

$$\frac{12 \times (\mathbb{E}[\text{Payout} \mid \text{Imported}] - \mathbb{E}[\text{Payout} \mid \text{Domestic}])}{\mathbb{E}[\text{Vehicle Cost} \mid \text{Imported}] - \mathbb{E}[\text{Vehicle Cost} \mid \text{Domestic}]} = 0.12$$

which is similar to the HLDI result, but a bit higher. We think this is possible because Korea is much more urbanized than the overall U.S., so the accident rate can be higher than in the U.S. overall, which can generate this result.

We now demonstrate that using collision insurance data provides a reliable benchmark for liability insurance data. According to an article on collision insurance payouts referenced during a congressional hearing in Korea,⁹ the average payout per accident for imported vehicles is 2.5 times higher than for domestic vehicles (imported: 3,279,000 KRW, domestic: 1,230,000 KRW). This is very similar to the payout ratio per accident from liability insurance, which is 2.53 (imported: 1,140,000 KRW, domestic: 2,891,000 KRW). This consistency suggests that collision insurance data can

⁹<https://mdtoday.co.kr/news/view/179570721763454>

reliably be used as a proxy for liability insurance data.¹⁰

B Estimation details

We relied on discretization of continuous variables to estimate our demand model. We set 30 grid points for each of θ , e_i , and $p(\theta)$, and 150 grid points for α_i . Regarding the nonparametric estimation of alpha distribution $f_\alpha(\cdot)$ —for given r , backing out the distribution of $f_\alpha(\cdot)$ that gives rise to $f_{\text{Athey-Imbens}}^{\text{no reform}}(\theta)$ —we showed in Section 7.1 that there is a unique α_i that rationalizes the chosen $\theta_i = (\frac{1.10}{\alpha_i})^{\frac{1}{r-1}}$ under the *no reform* scenario. However, due to discretization, for given r and θ , the α_i that rationalizes θ_i typically is not contained among its grid points. To address this, we select the value of α from its grid that results in θ' on its grid closest to θ . Figure 9 shows that the procedure works well: $f_{\text{Athey-Imbens}}^{\text{no reform}}(\theta)$ is replicated perfectly by our simulated $f_{\text{simulated}}^{\text{no reform}}(\theta|\hat{f}_\alpha(\cdot; \hat{r}), \hat{r})$.

To achieve global minimization of our criterion function (2)

$$\min_{r, \sigma_e, k} \sum_{\theta, p} \left[f_{\text{obs}}^{\text{actual}}(\theta, p) - f_{\text{simulated}}^{\text{actual}}(\theta, p | \hat{f}_\alpha(\cdot; r), \sigma_e, r, k) \right]^2,$$

we utilized Matlab's genetic algorithm solver. Figure 10 compares $f_{\text{obs}}^{\text{actual}}(\theta, p)$ and $f_{\text{simulated}}^{\text{actual}}(\theta, p | \hat{f}_\alpha(\cdot; r), \sigma_e, r, k)$. Figure 11 and Figure 12 show the estimated distribution of $\hat{f}_\alpha(\cdot; \hat{r})$ and $\hat{f}_e(\cdot)$.

¹⁰<https://www.seoulfn.com/news/articleView.html?idxno=337588>

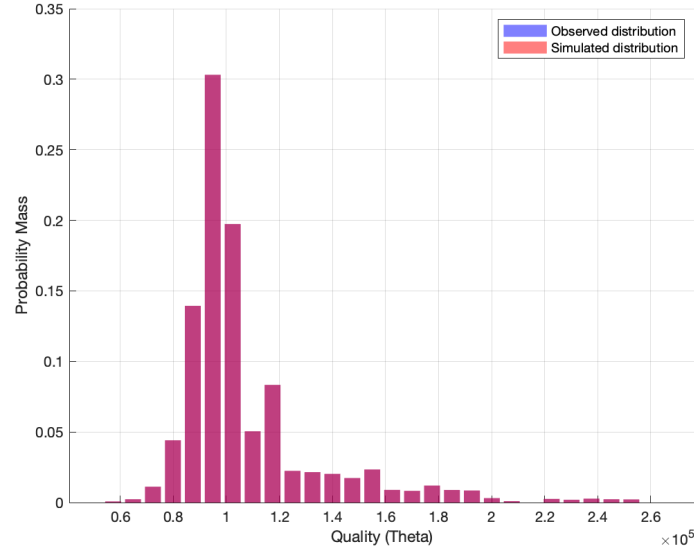


Figure 9: Observed and Simulated Distribution of θ under No Reform

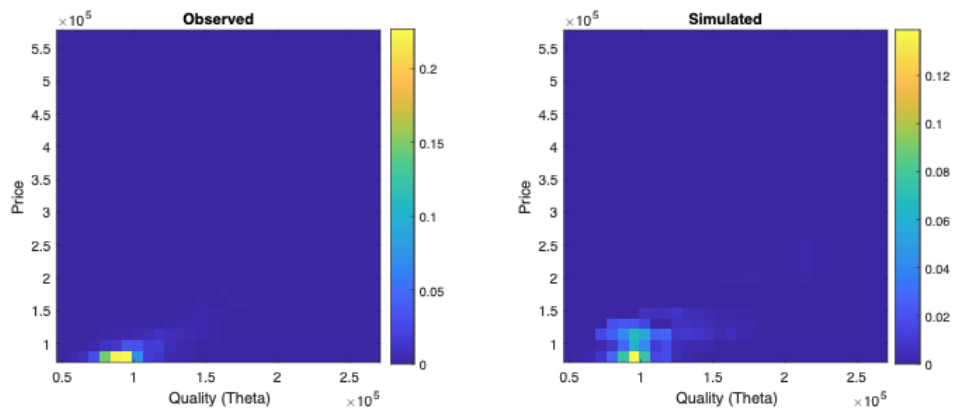


Figure 10: Observed and Simulated Distribution of (θ, p) under Actual Reform

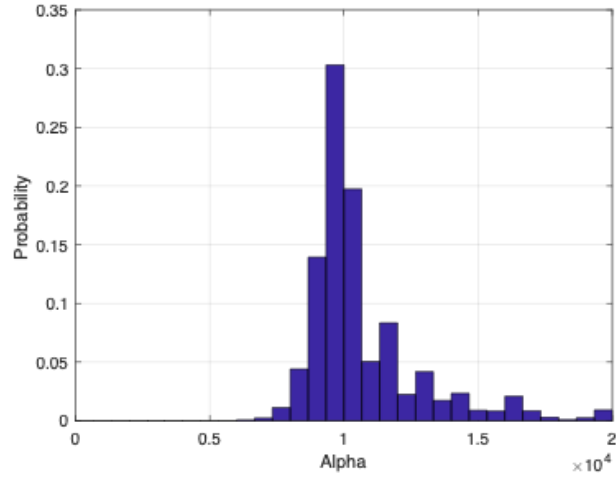


Figure 11: Estimated α Distribution

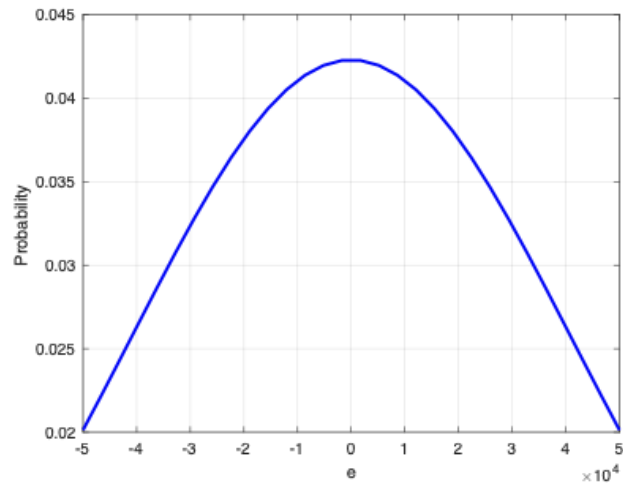


Figure 12: Estimated e Distribution