When Manufacturers Become Resellers: An Examination of the Strategic Interplay Between New and Used Car Pricing

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Abstract

Manufacturers of durable goods have an incentive to weaken secondary markets to reduce substitution away from their new products. The resale value offered in the secondary market, however, can benefit primary firms by lowering the net cost of new products. This paper documents how manufacturers' strategic intervention in the secondary market can enhance the perceived value of their primary products. I exploit an exogenous policy shift in South Korea's automobile industry that removed the used car sales ban by manufacturers. Using vehicle identification number (VIN)-level administrative microdata on new and used vehicle registrations, I find that for products where primary and secondary markets are sufficiently segmented—goods with high depreciation—primary firms offer higher trade-in prices than independent sellers in the secondary market. In contrast, when used goods retain their value—goods with low depreciation—this value is already reflected in the initial prices of new goods, leaving firms with no incentive to pay premiums. This strategy allows manufacturers to charge higher prices for new cars, exclusively for models where they offer premium trade-in prices in the secondary market.

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1 Introduction

Manufacturers of durable goods often face challenges due to the existence of secondary markets. Secondary markets can siphon off customers who might otherwise buy new products, resulting in reduced profitability for the manufacturers of new products (Miller, 1974; Rust, 1986; Porter and Sattler, 1999). Chen et al. (2013) find that, within the U.S. automobile industry, transitioning from a closed to frictionless secondary market resulted in a 35% reduction in manufacturers' profits. Schmitt and Shi (2018) document a 42% profit decrease in the textbook industry due to the resale of used textbooks, despite efforts to mitigate this through frequent revisions. Shiller (2013) reveals while digital goods offer opportunities to restrict resale, firms still face challenges in balancing consumer access and profitability.

Manufacturers commonly adopt strategies to counteract the adverse effects of secondary markets. One such strategy is planned obsolescence, where firms introduce new products frequently to make existing ones appear outdated, thereby encouraging consumers to purchase the latest model (Bulow, 1986; Waldman, 1993; Iizuka, 2007; Saengchote and Nakavachara, 2018). For instance, college textbook publishers attempt to eliminate the resale of used textbooks by introducing annual edition changes (Miller, 1974; Chevalier and Goolsbee, 2009; Schmitt and Shi, 2018). Another strategy involves deliberately reducing the durability of products to encourage repeat purchases (Rust, 1986). A historical example of this is the Phoebus cartel in the 1920s, where major light bulb manufacturers, including General Electric, Osram, and Philips, agreed to limit the lifespan of their bulbs to 1,000 hours, despite having the technology to produce longer-lasting bulbs.[1] Digital rights management (DRM) is another tool employed in recent years to make the resale, distribution, and sharing of products technically impossible (Johnson, 2011). Electronic Arts (EA) implemented online passes or digital-only releases to curb the resale of physical game discs, ensuring that each user has to purchase a new soft copy directly from the publisher.

These strategies, however, are not always optimal as consumers may gravitate toward products with lower net ownership costs. For instance, Intel made its 12th generation CPUs incompatible with existing motherboards, forcing PC users to purchase new motherboards to upgrade their CPUs. This

[1]The practice of reducing bulb lifespan is different from intentionally damaging products to price discriminate, as discussed by Deneckere and McAfee (1996). Deneckere and McAfee (1996)'s approach could potentially benefit consumers unwilling to pay for higher-quality goods. Instead, the Phoebus cartel's goal was to lower operational costs and increase the frequency of bulb replacements. For more details on how quality-differentiated product affects market dynamics, see, for example, Mussa and Rosen (1978), Moorthy and Png (1992), and Johnson and Myatt (2003).

resulted in consumer dissatisfaction and a substantial demand shift toward AMD's CPUs, which offered longer compatibility by maintaining the same socket across generations.[2] Similarly in the smartphone industry, Apple faced backlash for its practice of slowing down older iPhone models through software updates, which was perceived as a tactic to push consumers toward buying new models. This led to consumer frustration, lawsuits, and a subsequent decrease in brand loyalty.[3] Another example is the automotive industry, where certain car manufacturers have been criticized for introducing minor model updates annually, which diminishes the value of older models. Consumers, recognizing this pattern, may shift their preference to brands that offer longer product cycles or better resale value, seeking to minimize net operating costs.

Despite the challenges posed by secondary markets, the presence of a secondary market can also serve as a supportive feature—the resale value of their products—for the original producers. Resale value refers to the price that a used product can fetch in the secondary market after it has been purchased and used for some time by a consumer. This value not only affects how much consumers can recoup of their initial costs by selling their used goods, but it also determines their willingness to pay for new products (Haile, 2001; Oraiopoulos et al., 2012). When consumers anticipate the potential resale opportunity, they incorporate this factor into their original purchasing decisions, which can either increase or decrease their willingness to pay for new goods (Hendel and Lizzeri, 1999; Chevalier and Goolsbee, 2009; Bennett et al., 2015). The higher the resale value, the lower the net cost of the new product, making consumers more inclined to pay a higher initial price (Schmitt and Shi, 2018).

In this paper, I examine the mechanisms through which durable goods manufacturers participate as buyers in the secondary market to influence the resale value of their differently depreciating products. The specific method of this participation is through trade-in programs where manufacturers buy back used goods from consumers by offering them credit toward new purchases. This involvement equips original producers with an additional strategic variable: the ability to influence resale values of their products through their own buyback offers, rather than relying on prices set by independent sellers in the secondary market. Manufacturers' decisions to adjust the resale value

[2] `https://www.techpowerup.com/forums/threads/intel-alder-lake-has-compatibility-issues-with-older-versions-of-denuvo-drm-middleware.287986`, accessed August 2024.

[3] Ziady, Hanna, "Apple faces lawsuits in Europe over slowing down older iPhones," *CNN*, December 2, 2020, `https://www.cnn.com/2020/12/02/tech/apple-iphone-slowing-europe-lawsuit/index.html`, accessed August 2024.

of their own used products involve evaluating whether the benefits of the indirect demand effect in the primary market outweigh the costs of paying above the benchmark price predominantly set by sellers in decentralized secondary markets. When the resale value of a product is sufficiently high, customers can recoup a significant portion of their cost when purchasing new items, but the close substitutability between new and used items can lead to strong cannibalization between these goods. When the resale value is low, the distinct segmentation between primary and secondary markets may mitigate cannibalization, but consumers might be attracted to competitors' similar products with higher resale values. In equilibrium, firms strategically determine the optimal resale prices to balance the negative impact of cannibalization with the benefits of increased resale value.

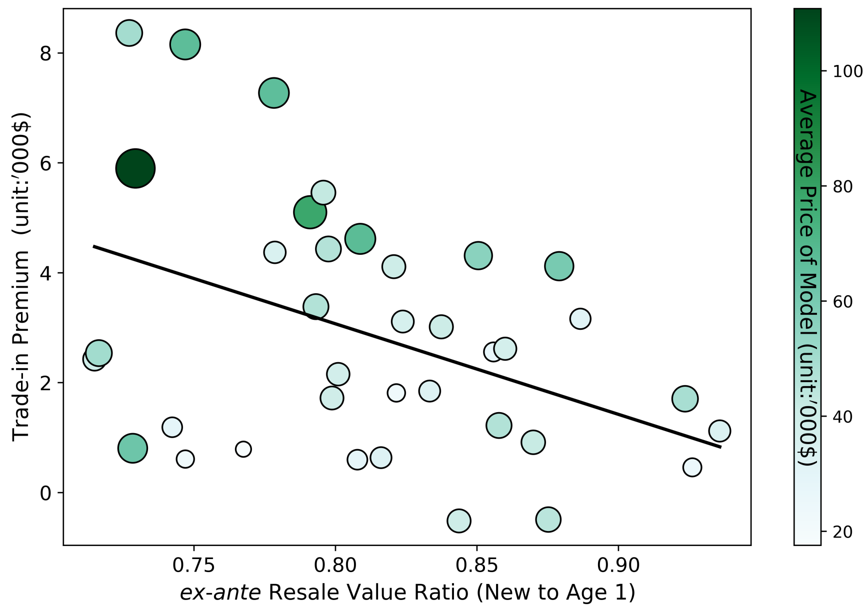
I find this mechanism has empirical support. To assess this, I exploit a natural experiment induced by a recent exogenous policy change in the South Korean automobile industry—the sale of used vehicles by original auto manufacturers was prohibited to protect the profits of small independent used car dealers.[4] The repeal of this protective ban authorized Hyundai Motor Group, which has held 70% of the new car market share for the past two decades, to implement trade-in programs in the secondary vehicle market.[5] Through this trade-in program, Hyundai now has the ability to *endogenously* determine the resale value of their products by purchasing their old products from used car owners, a capability that was previously determined *exogenously* out of Hyundai's control. Using vehicle identification number (VIN)-level administrative registration data which includes comprehensive characteristics of all new and used cars registered from 2017 to 2024, I first identify Hyundai's trade-in prices. I then analyze how their incentives for price premiums vary across different models of vehicles and provide the effects of their intervention on the new automobile market.

I document that the *ex-ante* depreciation rates of different vehicle models play a significant role in manufacturers' incentives to offer price premiums (i.e., offer higher wholesale prices than dealers in a competitive market). The results indicate that Hyundai pays wholesale price premiums for vehicles that depreciate quickly in the secondary market, such as the luxury car models of G80. When consumers place a high value on newness relative to usedness, they prefer new items over used ones,

[4] South Korea has no franchise law as in the U.S., which often presents unique challenges for research on U.S. automobile pricing. Prior to policy change in Korea, automakers sold new cars directly to consumers and used cars were solely sold by independent dealers in a decentralized secondary market. The advantages of studying the Korean automobile market from the perspective of pricing decisions will be discussed in Section 3.

[5] Hyundai Motor Group produces cars under the brands Hyundai, Kia, and Genesis. Throughout this paper, I will use the term "Hyundai Motor Group" to refer to all three brands as a whole, and "Hyundai" to indicate one of three brands Hyundai Motor Group produces.

Figure 1. Retained Value (New to Age 1) and Trade-in Premium

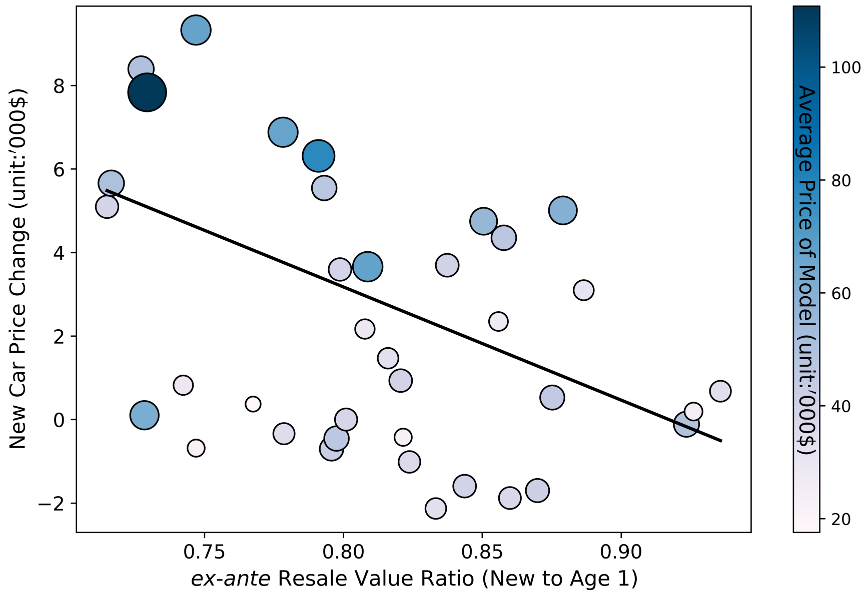


Note: I display the relationship between trade-in premiums and resale value across 37 vehicle models, aggregated from 2,742 cars. The x-axis represents the resale value ratio of first-year cars *before* Hyundai's entry, and the y-axis shows the difference in wholesale prices between Hyundai and independent dealers. Detailed descriptions of variable construction can be found in Section 5.

leading to lower and rapidly declining secondhand prices. In this case, the primary and secondary markets remain sufficiently distinct, minimizing cannibalization between new and used goods. As a result, manufacturers can capitalize on the increased resale value of used goods by offering price premiums, as these resale values are not fully reflected in the initial prices of new goods. Conversely, Hyundai is less likely to offer price premiums for vehicles that maintain high resale value and depreciate slowly in the secondary market, such as the compact car models of Elantra. When the perceived value between new and used goods is minimal, consumers may be willing to pay nearly as much for used items as they would for new ones, leading to a more robust secondary market with higher prices. This higher value of used goods is already embedded in the prices firms can charge for new products, as consumers are prepared to pay a premium upfront, knowing they can recoup a significant portion of their costs upon resale. In such cases, offering high trade-in values is less beneficial for manufacturers, as the additional costs do not translate into higher profits in the primary market.

Figure 1 and Figure 2 illustrate preliminary evidence of the main findings. The figures display scatter plots of 37 vehicle models (aggregated from 2,742 cars) that Hyundai acquired, with the size and color of each dot representing the average price of the respective vehicle model. The x-axis of both figures indicates the ratio of value retained as the vehicle ages from new to one year *before*

Figure 2. **Retained Value (New to Age 1) and Price Change of New Cars in Post-Entry Period**



Note: I display the relationship between new car price change and resale value across 37 vehicle models, aggregated from 2,742 cars. The x-axis represents the resale value ratio of first-year cars *before* Hyundai's entry, and the y-axis shows the changes in new car prices *after* Hyundai's entry. Detailed descriptions of variable construction can be found in Section 5.

Hyundai's entry, and thus, orthogonal to Hyundai's decision. The y-axis in Figure 1 is the premium Hyundai paid above the dealers' wholesale price and in Figure 2 the change in new car prices for each model *after* Hyundai's engagement in the secondary market. Figure 1 demonstrates that Hyundai tends to offer lower premiums for vehicles that retain their value well during the first year, while offering higher premiums for those that depreciate rapidly. Figure 2 suggests that models with higher depreciation saw the most significant increases in new car prices, with more expensive models driving this trend, indicating that Hyundai's entry has a pronounced effect on the pricing of higher-end vehicles.

To quantify these results, I estimate that Hyundai pays an additional \$1,648 more than dealers in a decentralized used car market for vehicle models with a 10% higher first-year depreciation rate, reflecting a targeted approach to enhance the resale value of models that depreciate rapidly. This strategic adjustment in trade-in prices appears consistent with Anderson and Ginsburgh (1994), showing that intervention from original producers would yield the most pronounced effects on rapidly depreciating products. While the overall change in new car prices across all Hyundai brands (including Hyundai, Kia, and Genesis) was not statistically significant, a closer look at the model-level data reveals that only Genesis models experienced a substantial price increase of 2.76% (equivalent to

$2,703) following Hyundai's entry into the secondary market. This suggests that Hyundai's engagement in the resale market was particularly effective for its luxury brand, where there was greater scope to leverage improvements in perceived resale value to elevate new car prices—an effect that would have been overlooked in an aggregate-level analysis across all brands or models.

The results of this paper underscore the strategic role of manufacturers within secondary markets to enhance primary market profitability. Prior research has explored how the presence of secondary markets for various goods generates incentives that influence product durability (Liebowitz, 1982; Rust, 1986; Esteban and Shum, 2007), product valuation (Bennett et al., 2015), market segmentation (Hendel and Lizzeri, 1999), auction bidding (Haile, 2001), and quantity produced (Feng et al., 2019). Secondary markets can allow firms to implement price discrimination, enabling them to segment the market and extract additional consumer surplus (Anderson and Ginsburgh, 1994). Firms may employ strategies such as leasing to mitigate competition between new and used goods (Waldman, 1997; Desai and Purohit, 1999) or segmentation of secondary markets to appeal to primary market consumers (Hendel and Lizzeri, 1999). Moreover, firms in industries like IT hardware charge relicensing fees to balance additional revenue and curtailing sales from secondary markets (Oraiopoulos et al., 2012). Building on these insights, this research is the first to examine how firms react to a marketplace environment when they transition from single pricing strategy (i.e., pricing for new products) to two pricing strategy (i.e., pricing for new and used products). This paper contributes to the current literature by providing empirical support, using variations arising from a natural experiment, on how durable goods manufacturers have strategic incentive to manage resale values of their products, and its impact on their primary market products. This research extends the understanding of how manufacturers can transform the **challenges** posed by secondary markets into **opportunities** for enhancing primary market performance.

The remainder of this paper is organized as follows: Section 2 introduces the analytical framework. Section 3 introduces the policy change in South Korea used to examine the empirics. Section 4 discusses the data, and Section 5 presents the main results. Section 6 explores alternative mechanisms. Section 7 concludes.

2 A Simple Model of Durable Goods

This section presents a simplified two-period model of automobile purchasing to capture the incentives and behaviors of key players in both the new and used car markets. The model aims to illustrate the strategic adjustments manufacturers make when they are allowed to participate in the secondary market through trade-in programs. The focus is on understanding how manufacturers' pricing strategies may shift in response to this new opportunity.

The framework used in this section is similar to the models developed by Oraiopoulos et al. (2012) and Li et al. (2019). Manufacturers sell new cars in the first period, which become used cars in the second period, and vanish afterward. Consumers live for two periods and decide whether to buy a new or used car in each period. Consumer utility is uniformly distributed over their type $\theta \in [0,1]$, which represents their heterogenous willingness to pay for a new car. The vehicle's depreciation is captured by its durability $\delta < 1$, where $\delta\theta \in [0, \delta]$ reflects the consumer's valuation of a used car as it transitions from new to used over time, without any refurbishment by dealers.[6] On the other hand, refurbished cars offer a higher perceived value δ_r where $\delta < \delta_r < 1$, due to the refurbishing process. This refurbishment incurs a cost c_r, which includes expenses such as replacing worn-out parts, professional cleaning, document fees, and the dealer's accounting profit. Additionally, w represents the resale value that consumers receive when selling their car after one period use of a new car, and c denotes the production cost of a new car.

Consumers are segmented into three groups based on their choices over two periods. First, there are consumers who buy new cars in both periods, denoted as nn, whose utility is: $U_{nn} = \theta - p + w + \theta - p + w$. These consumers purchase a new car at price p in the first period, sell it for the resale value w, and repeat the process in the second period. While they may not live beyond the second period, the resale value w is typically left to their family or estate. Second, there are consumers who buy a new car in the first period and continue using it as a used car in the second period, denoted as $n0$, whose utility is: $U_{n0} = \theta - p + \delta\theta$. Finally, there are consumers who buy a used car from independent dealers, denoted as uu, with the utility function: $U_{uu} = \delta_r\theta - p_u + \delta_r\theta - p_u$. These consumers form overlapping generations, where each generation experiences two periods. New cars in the first period become used cars in the second period, creating six distinct demand segments:

[6] Li et al. (2019) define consumers' willingness to pay for secondary goods as uniformly distributed over $\theta \in [0, b]$, where $b \leq 1$. In contrast, I use δ to explicitly capture the durability parameter of a new car, which reflects one minus the depreciation over time.

$q_{\mathbf{n}n}, q_{\mathbf{n}0}, q_{\mathbf{u}u}$ from the current generation, and $q_{n\mathbf{n}}, q_{n\mathbf{0}}, q_{u\mathbf{u}}$ from the previous generations. For a given period, when the first-period consumers of the **current** generation decide whether to buy a new or used car, the second-period consumers of the **previous** generation must choose whether to continue using their existing vehicle, buy a new car, or buy a used one. In each period, the manufacturer and independent dealers must cater to the combined demand from both generations. This interaction shapes the competition between the new and used car markets. For simplicity, I normalize the total market size for each generation to 1.[7]

Dealers operate as price-takers under a Bertrand-Nash framework, taking the market's cost parameters as given and setting used car prices equal to their marginal costs. Thus, they do not attempt to optimize prices. Rather, their role is to merely transfer the ownership of a car from the previous owner to the new buyer, acting as intermediaries in the market.[8] The manufacturer' profit maximization problem involves setting the new car price p. The profit function includes the demand for new cars in both periods, $q_{n\mathbf{n}}$ and $q_{\mathbf{n}n}$, and the demand for continuing consumers q_{n0}, with the following objective:

$$\max_p \Pi_m(p) = (p - c)(q_{nn} + q_{nn} + q_{n0})$$

subject to:

$$q_{nn} \geqq 0, \quad q_{n0} \geqq 0, \quad q_{uu} \geqq 0$$

Manufacturer Entry into the Secondary Market

After the manufacturer enters the secondary market, a new consumer segment emerges: those who trade in their cars to the manufacturer at the end of each period, and receive $w + \alpha$. When these

[7]This assumption is typically used in durable goods studies such as Rao et al. (2009), Miao et al. (2017), and Li et al. (2019)

[8]Even though dealers do not strategically maximize their profits, their objective can be written as:

$$\Pi_d = (p_u - c_r - w)(q_{u\mathbf{u}} + q_{\mathbf{u}u})$$

where p_u represents the price at which dealers sell used cars, c_r is the refurbishment cost incurred by the dealers, and w is the resale value that they pay when purchasing the used cars. To simplify, I assume dealers can always purchase the used cars with the price of w from the market for sale. The term $q_{\mathbf{u}u}$ and $q_{u\mathbf{u}}$ represents the demand for used cars from the first period of young generation and second period of old generation, respectively. q_{nn} represents the supply of used cars, which originates from the consumers who bought new cars in the first period and decided to sell them. Importantly, I assume all used cars in the second period are supplied by consumers who bought new cars in the first period, meaning that the quantity of used cars available for sale is directly tied to the number of new cars sold. As a result, the following relationship $q_{\mathbf{n}n} = q_{u\mathbf{u}} + q_{\mathbf{u}u}$ holds. This equation reflects the balance between the supply and demand for used cars, with each unit of supply from q_{nn} satisfying the demand from two segments of q_{uu}. Since dealers are price-takers, their optimal selling price for used cars is simply given by $p_u = c_r + w$. Although dealers may not generate economic profit, their accounting profit is embedded in the refurbishing cost, c_r, which includes not only the expenses related to refurbishing and maintaining the vehicles, but also a margin that allows them to cover basic operations and opportunity cost.

consumers sell their used cars, they receive not only the resale value w but also a trade-in premium α, which may be positive or negative depending on the manufacturer's optimal decision. Importantly, I assume only a fraction λ of consumers can trade in their cars to the manufacturer, where $0 < \lambda < 1$. This is due to a market share cap λ imposed by the Korean government on manufacturers's participation in the secondary market. This will be explained in more detail in Section 3.

The new utility function for consumers who buy new cars in both periods becomes the expected utility of these terms as:

$$U_{nn} = (1 - \lambda) \cdot (2 \cdot (\theta - p + w)) + \lambda \cdot (2 \cdot (\theta - p + w + \alpha))$$

λ represents the share of new car owners selected to trade in their car to the manufacturer and receive $w + \alpha$ for their car, while $1 - \lambda$ is the the share of new car owners who will sell their car in the regular secondary market, receiving the resale value w. The manufacturer's profit maximization problem now changes, as it seeks to optimize both the price of new cars p and the trade-in premium α. The manufacturer's revised profit function is:

$$\max_{p,\alpha} \Pi_m(p, \alpha) = (p - c)(q_{nn} + q_{nn} + q_{n0}) - \alpha \cdot \lambda q_{nn}$$

subject to:

$$q_{nn} \geqq 0, \quad q_{n0} \geqq 0, \quad q_{uu} \geqq 0$$

where λq_{nn} represents the quantity of used cars traded in to the manufacturer. The trade-in premium α influences the manufacturer's per-vehicle cost for acquiring these used cars from consumers. For simplicity, it is assumed that manufacturers do not generate additional economic profit from reselling their own refurbished vehicles in the secondary market.[9] The key trade-off for the manufacturer is that while a higher α increases demand from the nn segment by incentivizing consumers to upgrade, it also raises costs by paying out more in trade-in process in the secondary market. Thus, the manufacturer should find the optimal level of α that encourages upgrades while managing the additional costs.

[9]While manufacturer-refurbished cars may be perceived as higher quality in practice, the costs associated with refurbishment can also be significant, potentially limiting any additional margins they could gain from reselling these vehicles. As such, potential profit gains from refurbished car sales may be minimal. Alternatively, this can be viewed as the manufacturer selecting a subset of consumers and either offering or extracting α without directly influencing the resale process.

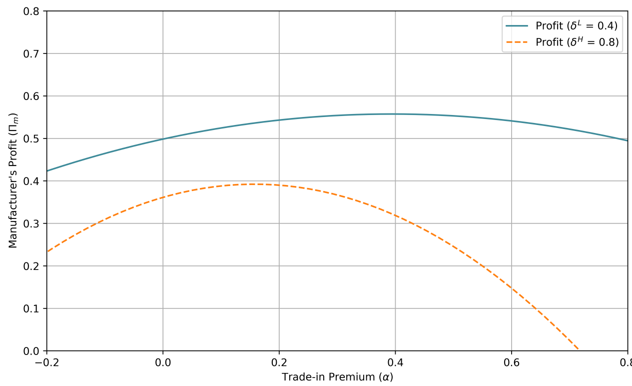
Discussion of Results

In this section, I examine the equilibrium properties of the manufacturer's pricing strategies in the primary and secondary markets, and analyze how their incentives change in response to key parameters. A distinctive feature of empirics of this research is the ability to observe durability of vehicles at the granular products level. Accordingly, in the theoretical analysis, I focus on how durabilities of different products influence the manufacturer's pricing incentives. Specifically, I consider two cases without loss of generality: one with low durability products ($\delta^L = 0.4$) and the other with high durability products ($\delta^H = 0.8$). By comparing these cases, I derive the following baseline insight:

OBSERVATION 1. *When manufacturers do not participate in the secondary market (i.e., $\alpha = 0$), their profit is higher when the product has low durability* ($\delta^L = 0.4$) *compared to high durability* ($\delta^H = 0.8$)

Figure 3 displays the graphical illustration of OBSERVATION 1. Observe that when $\alpha = 0$, manufacturer's profit Π_m is higher for $\delta = 0.4$ (orange dashed line) than $\delta = 0.8$ (blue solid line). This outcome is primarily driven by differing consumer responses to product durability. When durability is low, the car loses value more quickly, meaning consumers (especially q_{n0} segment) have a stronger incentive to replace their car with a new one. This leads to more frequent purchases of new cars, which increases new car demand and, consequently, the manufacturer's profit. On the other hand, when durability is high, the car depreciates more slowly, and consumers (especially q_{n0} segment) derive greater utility from holding on to their used cars for a longer period. As a result, consumers are less likely to replace their used cars with new ones, reducing the demand for new cars. This lower demand leads to reduced profits for the manufacturer. This finding aligns with conventional wisdom that reducing durability can increase a producer's profit by accelerating replacement cycles (Miller, 1974; Bulow, 1986; Rust, 1986; Waldman, 1993). By making products less durable, manufacturers encourage more frequent purchases, boosting overall sales turnover and profits. OBSERVATION 1 is consistent with the theory of vertical product differentiation (Shaked and Sutton, 1982; Anderson and Ginsburgh, 1994) that increasing the quality gap between low- and high-quality products—in this case, between used and new cars—creates distinct market segments.

Figure 3. Manufacturer Profit and Trade-in Premium ($\lambda = 0.5$)



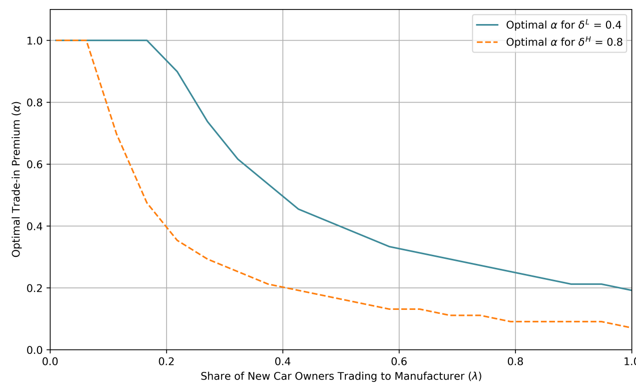
Note: The parameters are set to $\delta^L = 0.4, \delta_r^L = 0.42, \delta^H = 0.8, \delta_r^H = 0.82, c = 0.3, c_r = 0.0005, w = 0.24, \lambda = 0.5.$

By differentiating products based on quality, manufacturers can engage in price discrimination, appealing to different consumer groups with varying willingness to pay. This segmentation strategy allows manufacturers to capture more consumer surplus, enhancing profitability across market tiers.

PREDICTION 1. *When manufacturers participate in the secondary market (i.e.,* $\alpha \neq 0$*), the optimal trade-in premium* α *is higher when the product has low durability* $(\delta^L = 0.4)$ *compared to high durability* $(\delta^H = 0.8)$

Revisiting Figure 3, observe that the manufacturer's profit is maximized at around $\alpha = 0.15$ when the product has high durability ($\delta^H = 0.8$) and at around $\alpha = 0.39$ when the product has low durability ($\delta^L = 0.4$). PREDICTION 1 can be understood by the impact of product durability on consumer's incentives to upgrade and the manufacturer's corresponding pricing strategies. Due to the slow depreciation of the vehicle when $\delta^H = 0.8$, consumers derive greater utility from continuing to drive their durable car into the second period (i.e., strong demand in q_{n0}). For these consumers, the option of holding onto the car is attractive, and they are not as eager to trade it in as they would be with a fast-depreciating car. Thus, they need a significantly large financial incentive (i.e., a high trade-in premium α) to trade in their car, which is unprofitable from the manufacturer's perspective. Offering a high α would be costly for the manufacturer without a corresponding increase in the number of consumers willing to trade in their cars and buy new. This is shown in Figure 3 that the slope of the profit function ($= \partial \Pi_m / \partial \alpha$) is steeper when $\delta^H = 0.8$ than $\delta^L = 0.4$. The rapid decrease in revenue when δ^H compared to δ^L implies that higher trade-in premiums do

Figure 4. Trade-in Premium and Fraction of Trade-in Quantity



Note: The parameters are set to $\delta^L = 0.4, \delta_r^L = 0.42, \delta^H = 0.8, \delta_r^H = 0.82, c = 0.3, c_r = 0.0005, w = 0.24$.

not generate sufficient additional new car sales to justify the cost.[10] Thus, the manufacturer opts for a lower trade-in premium, knowing that not many consumers will trade in their car regardless of the premium offered. To put it another way, α can be interpreted as consumers' willingness to accept for transitioning into the q_{nn} segment from other segments. Even if the manufacturer offers a higher trade-in premium, consumers prefer to continue using their durable cars when $\delta^H = 0.8$, as the marginal utility gain relative to the durability (i.e., α/δ^H) appears quite small. This results in not worth the cost to the manufacturer. Conversely, when the product's durability is low ($\delta^L = 0.4$), consumers experience rapid depreciation, causing the value of their used cars to decline substantially over time. In this scenario, the relative utility gain from a trade-in (i.e., α/δ^L) appears more significant, leading consumers to be more responsive to changes in the trade-in premium α. From the supply side, an increase in α can effectively incentivize a large number of marginal consumers to trade in their rapidly depreciating vehicles, making it more beneficial for the manufacturer to offer a higher α in this case. This explains why the manufacturer offers a higher trade-in premium for fast-depreciating vehicles (δ^L) compared to slowly depreciating vehicles (δ^H): it helps capture a more responsive consumer base, encouraging trade-ins and enhancing profits.

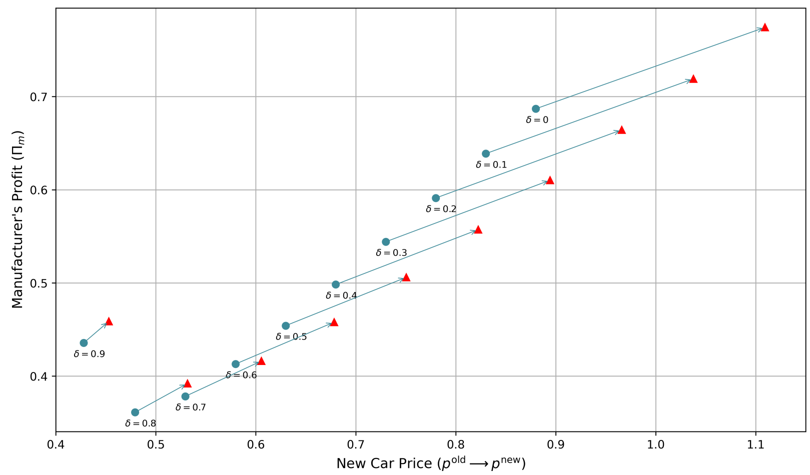
OBSERVATION 2. *The optimal trade-in premium (α) decreases as the share of new car consumers trading in (λ) increases, for both high and low durability products.*

The results from Figure 4 indicate that as the manufacturer gains more control over the secondary

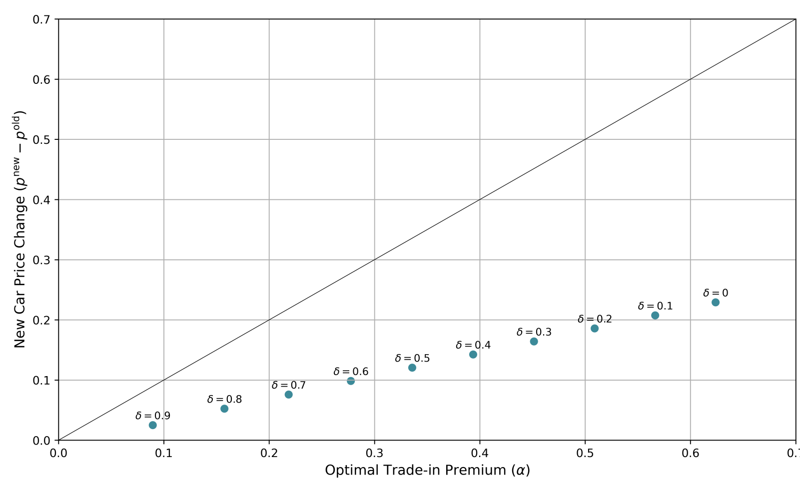
[10]This effect is even more pronounced when the manufacturer has full control over the secondary market (i.e., when $\lambda = 1$), as illustrated in Figure A1.

market (i.e., as λ increases), they can offer lower trade-in premium α. The underlying mechanism is straightforward: the greater the manufacturer's presence in the secondary market, the less they need to reply on offering generous trade-in premiums to entice consumers. When λ is low, only a small portion of new car owners trade in their vehicles, so the manufacturer must offer a higher premium to encourage upgrades. This premium serves as a tool to capture consumers who might otherwise hold onto their vehicles or sell them through the independent channels. However, as λ increases and a large fraction of consumers trade in their cars, the necessity of offering a high premium declines. Importantly, the relative difference in the optimal α between high- and low-durability products persists even when λ increases, reflecting the consistent and robust results in Figure 3.

Figure 5. Impact of Manufacturer Entry on Price Changes in Primary Market



(a) Price Variation Between No-entry and Entry Scenarios



(b) Trade-in Premium's Influence on New Car Pricing Adjustments

PREDICTION 2. *When manufacturers participate in the secondary market (i.e., $\alpha \neq 0$), new car price p and manufacturer profit Π_m increases but this increment diminishes in durability δ*

The graphs in Figure 5 illustrate how the new car price changes after manufacturer entry with corresponding optimal level of trade-in premium α across different durability level of products. First in Figure 5(a), the transition in price and profit before and after Hyundai's entry into the secondary market is shown, with arrows connecting the original (green circle) to the new (red triangle) scenarios for different δ levels. After Hyundai's entry, profits and prices increase, particularly for products with lower δ. Fast-depreciating products see more significant increases in both profit and price due to higher trade-in premiums, while slow-depreciating products experience more modest adjustments, as they require less aggressive trade-in incentives. Figure 5(b) depicts the relationship between the trade-in premium (α) and the new car price change ($p_{\text{new}} - p_{\text{old}}$), with each point representing different δ levels. As α increases, the new car price tends to rise. However, the magnitude of the price increase depends on δ. For lower δ values, where products depreciate quickly, the price difference is larger, reflecting greater responsiveness to trade-in offers. Conversely, higher δ values lead to smaller price changes, as more durable products require less incentive for trade-ins. In summary, both graphs emphasize the role of product durability (δ). Lower δ values lead to larger trade-in premiums, greater price changes, and higher profits, while higher δ values involve more modest adjustments across all factors.

3 Institutional Background

3.1 The Regulatory Changes in South Korea's Secondary Vehicle Market

South Korea, as the world's fifth-largest automobile producer, offers a unique context for studying how manufacturers manage the resale value of their products. First, a recent policy shift provides an opportunity to examine the exogenous entry of manufacturers into the used car market. In 2011, the Korea Commission for Corporate Partnership (hereafter referred to as the Commission) enacted the Suitable Business for Small- and Medium-sized Enterprises (SBSMEs) Act. This legislation was designed to protect SMEs in industries where the entry of large conglomerates could significantly harm small businesses (Guner et al., 2008; Kim, 2011; Lee, 2015b; Hwang and Han, 2014).[11] Industries designated under the SBSMEs protection could enjoy a minimum of three years and up to six years of restricted competition. After this period, they could be reviewed for designation as Suitable Business for Micro Enterprises (SBMEs), offering a second layer of protection against conglomerate entry (Park, 2011; Lee, 2015a).

The used car sales industry was designated as SBSMEs in March 2013, prohibiting non-SMEs from expanding their market share or entering the used car sales business anew. During the six-year protection period, the number of used car sales firms increased by 24.9%, from 5,092 in 2013 to 6,361 in 2018, while total gross sales more than doubled from $4.9 billion to $12.4 billion.[12] After the SBSMEs protection expired, the industry applied for SBMEs designation. However, on March 17, 2022, after a three-year review, the Commission decided not to reassign the industry, effectively removing used car sales from the list of protected sectors.

A key motivation behind this decision was the persistent issues of informational frictions in the secondary vehicle market. The Commission observed that the used car market suffered from significant information asymmetry, where independent small-sized dealers often lacked transparency about vehicle conditions. Consumers frequently faced deceptive practices, such as undisclosed defects or tampered odometers, leading to a severe "lemons" problem that eroded trust in the market. By allowing manufacturers to enter the used car market, the government aimed to mitigate these issues. Manufacturers are better positioned to certify pre-owned vehicles, provide warranties, and ensure higher standards of quality and transparency. Their entry was expected to reduce information asymmetry, enhance consumer confidence, and ultimately improve market efficiency. Additionally, the Commission noted that, compared to other SBMEs-designated industries, the used car sales industry had a smaller proportion of small businesses, higher average annual sales, and fewer unpaid family workers. They concluded that the market had matured to a point where the benefits of increased competition and improved consumer protection outweighed the advantages of continued protectionism.

Following the repeal, Hyundai Motor Group, Korea's largest automotive manufacturer, promptly moved to enter the secondary vehicle market. After initial negotiations between Hyundai and the

[11] According to Article 2, Paragraph 1 of the 'Framework Act on Small and Medium Enterprises,' SMEs are companies that meet both of the following criteria: (i) total assets less than 500 billion Korean won, and (ii) average annual sales of 100 billion Korean won or less. Companies exceeding either criterion are classified as conglomerates.

[12] Source: KOSIS, National Business Survey

used car dealers' association failed in March 2022, the Ministry of SMEs and Startups (MSS) intervened and brokered a resolution in May 2022. The agreement allowed Hyundai Motor Group to commence their used car sales business starting January 1, 2023, with market share limitations for three years.[13] Hyundai and Kia also announced that they would only sell used cars that are less than five years old and have mileage under 100,000 km. These thresholds are used to identify Hyundai's trade-in vehicles in the dataset. Ultimately, Hyundai officially entered the secondary vehicle market in October 2024.

3.2 Vertical Arrangement between Manufacturers and Dealerships

The vertical structure of the automobile markets in the U.S. and South Korea differs significantly in how vehicles are priced and sold, providing a clear and advantageous research setting. In South Korea, the price observable to researchers and consumers is the actual transaction price, which is equal to the manufacturer's suggested retail price (MSRP), leaving no room for dealer price adjustments. This allows for a more precise study of how manufacturers manage the resale value of their products in the secondary market. According to Johnson (2017)'s categorization of vertical relationships between upstream and downstream firms, the U.S. *new* car market operates under a "wholesale" model. In this system, local dealers, acting as downstream firms, purchase new vehicles at a per-unit wholesale price from auto manufacturers, who are the upstream firms. Ownership of the vehicles transfers to the dealers, who then have the autonomy to set the retail prices for consumers. In contrast, South Korea's new car market follows an "agency" model, where the relationship between manufacturers and dealers is fundamentally different. Dealers of new cars are employees of the manufacturers—rather than purchasing the cars, they receive a paycheck or fixed commission from the manufacturers. The upstream firm, the car manufacturer, retains entire control over the pricing of vehicles. The retail prices are set by the manufacturers themselves, and dealers have no discretion in setting the new car prices, similar to how Apple sells its products through its own stores in the U.S. This direct-to-consumer (DTC) approach is also pursued by companies like Tesla and other electric

[13] The specifics of their market share cap are as follows: From January 1, 2023, to April 30, 2023, both Hyundai and Kia could sell up to 5,000 used cars. From May 1, 2023, to April 30, 2024, Hyundai and Kia could sell up to 2.90% and 2.10% of the total used cars sold in the previous 12 months, respectively. From May 1, 2024, to April 30, 2025, Hyundai and Kia could sell up to 4.10% and 2.90% of the total used cars sold in the previous 12 months, respectively. Since the number of cars they sold was well below these caps, the limitations did not pose a significant constraint. However, my analysis suggests that even a small share of secondary market presence by the manufacturer can have a meaningful impact on the primary market.

vehicle manufacturers in America.

In the U.S., direct sales by automakers to consumers are largely restricted by franchise laws in most states, which require new cars to be sold only through licensed, independently owned dealerships. These laws, which date back to 1889, have historically prohibited automakers from directly selling their vehicles to consumers. The National Automobile Dealers Association argues that this franchise dealership model provides consumers with added protection in the marketplace, as it allows local businesses to compete for the best prices (Keller and Elias, 2014). In contrast, South Korea's auto market allows manufacturers to directly sell cars to consumers, fully adopting the DTC approach. This contrast is less pronounced in the used car markets of both countries. In the U.S., dealers continue to control pricing, setting both retail and wholesale prices based on market conditions and their own strategies. Similarly, in South Korea, independent used car dealers retain discretion over both retail and wholesale pricing.

The implications of unique vertical arrangements in South Korea present a unique opportunity to study the direct pricing strategies employed by manufacturers. In the U.S., the wholesale model introduces complexities in analyzing automotive pricing due to the varying strategies and local market power of numerous independent dealers. In contrast, South Korea's agency and DTC models provide a more streamlined and transparent environment where pricing strategies for new cars (and now used cars as well) are globally set by manufacturers. This allows researchers to carefully examine how manufacturers control the resale value of their products in a nationwide market and provide a unique opportunity to study these strategies in a more controlled setting.

4 Data

The primary dataset used in this research is the micro-level vehicle registration data provided by the Ministry of Land, Infrastructure and Transport (MOLIT) in South Korea, which serves an administrative role analogous to the U.S. Department of Transportation (DOT). MOLIT holds comprehensive information on vehicle ownership changes, encompassing both new and used cars registered every month starting from April 2017.[14] The unit of observation (i.e., row) of the raw data is the vehicle

[14] In the U.S., vehicle title and registration serve distinct purposes—the title provides evidence of ownership, while registration indicates that a vehicle is officially listed within the state and authorized for use on public roads. Both documents are issued by the state's bureau of motor vehicles (BMV), but the title only needs to be updated when the vehicle changes owners. In contrast, in Korea, vehicle title and registration are combined into a single document. Henceforth in this paper, the terms "registration" and "title" are used interchangeably, and any change in a vehicle's registration indicates a change

identification number (VIN)-level, which is a unique 17-character code that identifies an individual motor vehicle. The data includes VIN with last 6 digits masked, vehicle brand (e.g., Toyota), model name (e.g., Camry), fuel type (e.g., hybrid), model year, manufactured date (month-year), transferred date (month-year), original sale price, transfer price, odometer reading, and various vehicle characteristics such as engine type, weight, size, etc.[15] The original sale price refers to the amount paid by the first owner of a vehicle to the manufacturer, while the transfer price denotes the price at which the vehicle is sold when it is subsequently transferred between owners. For new cars, the original sale price and the transfer price are the same, as the vehicle is being sold for the first time, and the manufacture and transfer dates coincide. In contrast, for used cars, the original sale price reflects the amount paid by the initial owner to the manufacturer, whereas the transfer price captures the amount paid by the current owner during the latest transaction.

The dataset also includes demographic information about the vehicle owner, such as age, gender, home address, and the location where the vehicle is used. A change in vehicle registration reflects a change in ownership, resulting in different data structures for new and used cars. For new cars, the initial sale involves a transfer of ownership from the manufacturer to the first buyer, capturing the demographic details of a single entity—either an individual or a business—the new car purchaser. In contrast, for used cars, ownership transfers involve two parties, allowing the data to capture demographic details of both the previous and new owners. This information is essential for distinguishing between vehicles acquired by Hyundai and those purchased by independent dealers or individual buyers.

4.1 Hyundai's Trade-in Cars

To identify Hyundai's trade-in vehicles, I utilized information on both the registered home address and the usage address, as described in the previous section. Specifically, Hyundai Motor Group's headquarters is located in Seocho, Seoul. I observed a substantial increase in the number of vehicles registered at Seocho starting in October 2023, coinciding with the launch of Hyundai's Certified Pre-Owned (CPO) car sales on their official website. This notable shift in registration patterns is further validated using Difference-in-Difference (DiD) estimation in Appendix B with various falsification

in car ownership.

[15] Other research that used similar administrative vehicle registration datasets in the U.S. include Gillingham et al. (2022) and Gillingham et al. (2023).

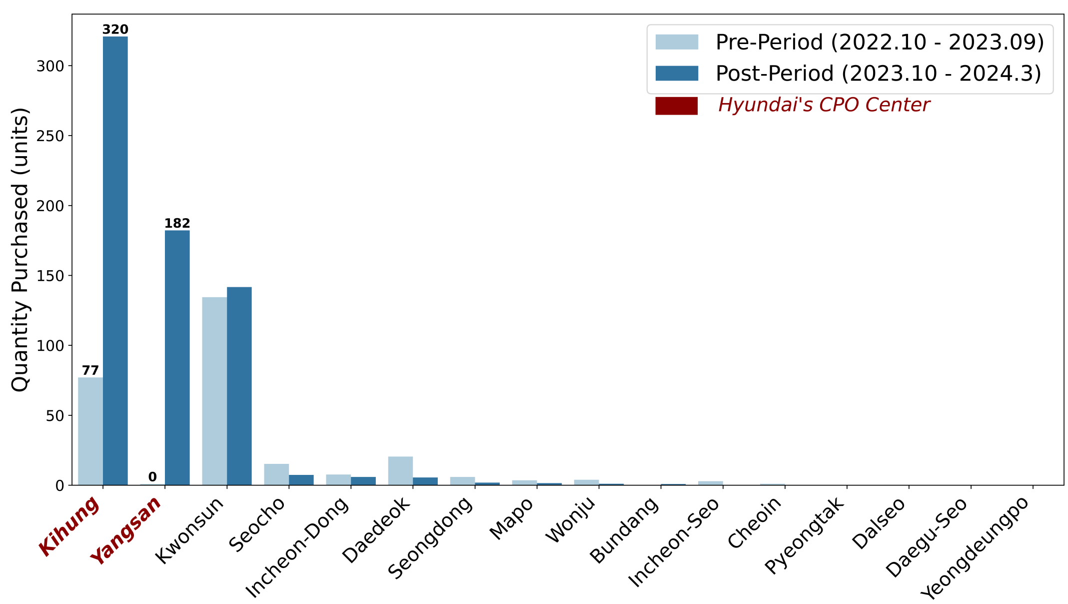
tests.

Among the vehicles with home addresses registered in Seocho, I also identified Hyundai's offline CPO centers located in Kihung and Yangsan. A marked increase in the number of vehicles used in these locations further supports the identification of Hyundai's trade-in vehicles in Figure 6. Therefore, I classify vehicles with a home address registered in Seocho and a usage address in either Kihung or Yangsan as Hyundai trade-in cars. Summary statistics of these identified vehicles are provided in Section 5.

4.2 Characterization of Resale Value Ratio

In South Korea, the sales price of a vehicle is the sum of two primary components: **the supply value**, which is the base price paid by the customer to the supplier, and **the value-added tax (VAT)**, which is set at 10% of the supply value. Figure 7 shows an example of a vehicle registration document, representing one row from my dataset. Observe that the supply value, listed in the bottom right corner, is recorded as 18,915,455 Korean won (approximately $18,915). Multiplying this amount by 1.1 (to account for the VAT) arrives at a total of 20,807,000.5 Korean won (approximately $20,807). This resulting figure is the integer amount that typically corresponds to the price tags displayed to consumers at the point of sale. While the sales price, inclusive of VAT, is the figure most commonly observed by consumers in both online and offline transactions, the original documentation records

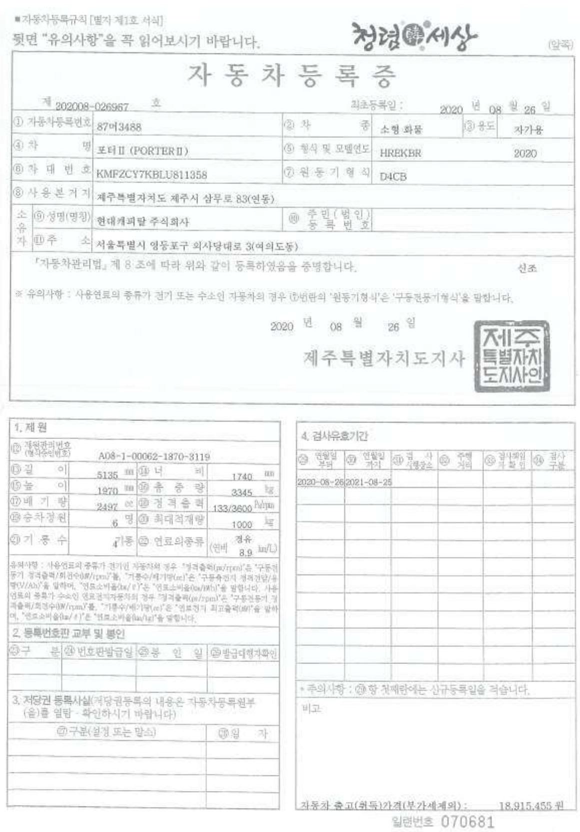
Figure 6. Surge in Vehicle Purchases at Hyundai's CPO Centers Post-Entry



only the supply value, as shown in Figure 7. This distinction is crucial because additional taxes, imposed by the government, are calculated based on the supply value rather than the total sales price. This method of tax calculation is designed to avoid the issue of double taxation. The additional taxes generally include a registration tax, which is approximately 7% of the supply value, and a bond purchase tax, which is around 1.15%. However, these rates can vary depending on the specific registration location of the vehicle and its fuel type. To ensure that the final cost paid by consumers is accurately reflected, I manually calculated the total price by adding these various taxes to different attributes of vehicles. This approach allowed me to determine the precise final car price, providing a more accurate foundation for analyzing vehicle pricing.

The calculation of the resale value ratio requires a nuanced understanding of the used car transaction price in my data. For used vehicles, the supply value represents the amount that the seller, or the previous owner of the vehicle, actually receives in her pocket. In a wholesale transaction involving a used car—where an individual car owner sells the vehicle to a dealer or to a manufacturer like Hyundai—the seller does not incur any additional taxes; instead, these taxes, such as the regis-

Figure 7. Example of Original Vehicle Registration Document



tration tax and bond purchase tax, are the responsibility of the buyer, who becomes the next owner of the vehicle. Therefore, when evaluating how much of the original new car price can be recouped through resale, the resale value ratio is computed by dividing the net amount the seller receives (the supply value) by the total cost of the new car, inclusive of all taxes. This retention ratio provides a measure of the financial return on a vehicle. Furthermore, the depreciation rate of a vehicle can be easily calculated as one minus the resale value ratio.

4.3 Descriptive Evidence on Low Resale Value of Hyundai's Luxury Brands

Table 1 presents the summary statistics of new car prices in South Korea from 2017 to 2024, which reveals significant differences in average prices among various manufacturers, particularly between Genesis, the luxury brand under Hyundai Motor Group, and major German luxury brands such as Mercedes-Benz, BMW, and Volkswagen. The average price of a Genesis vehicle is $69,760, positioning it as a premium option within the Hyundai Motor Group's portfolio. However, this pricing places Genesis as a less-valued luxury brand compared to the German counterparts, which are positioned similarly but command higher prices in the luxury market. For instance, BMW vehicles have an average price of $74,980, while Volkswagen vehicles average $84,150. Mercedes-Benz stands out with a significantly higher average price of $98,220, indicating its dominance in the ultra-luxury segment.

In terms of market share, Hyundai Motor Group overwhelmingly dominates the South Korean market, holding a 69.87% share. This dominance is largely driven by the combined sales of Kia and Hyundai, which together account for over 63% of the market. Despite its higher pricing, Genesis holds a smaller but significant market share of 6.56%, reflecting its positioning as a luxury brand within domestic auto manufacturers. On the other hand, the German brands collectively hold a 12.34% market share, with Mercedes-Benz and BMW leading at 5.00% and 4.92%, respectively. This indicates that while these German brands have a smaller presence compared to Hyundai Motor Group, they command a significant portion of the luxury vehicle market in South Korea.

Table 1 provides insights into the competitive dynamics of the South Korean automotive market. It highlights Hyundai Motor Group's dominance in terms of sales volume, while German brands maintain a strong presence in the luxury segment, leveraging higher average prices and a focus on premium offerings. It also suggests that Hyundai may have a strategic incentive to enhance the perceived value of its new cars, particularly the Genesis brand, in order to convince domestic

Table 1. **New Car Prices and Market Shares by Manufacturers (2017-2024)**

	New Car Prices (unit: ′000$)					Sales	
	Mean	**SD**	**p10**	**p50**	**p90**	**Count**	**Share**
Hyundai Motor Group							
Kia	34.07	13.44	16.38	33.91	49.89	3,306,280	31.73%
Hyundai	34.50	12.18	20.03	33.55	50.11	3,290,109	31.58%
Genesis	69.76	18.87	50.43	65.54	94.25	683,825	6.56%
Subtotal						7,280,214	69.87%
Other Domestic							
Renault Korea	30.12	4.94	23.78	30.29	36.04	442,505	4.25%
GM Korea	22.01	7.52	13.39	21.73	32.23	395,188	3.79%
KG Mobility	30.31	8.68	21.49	27.37	43.86	382,811	3.67%
Subtotal						1,220,504	11.71%
Germany							
Mercedes-Benz	98.22	51.18	56.92	81.52	173.05	520,511	5.00%
BMW Group	74.98	42.35	40.69	67.75	124.02	512,976	4.92%
Volkswagen	84.15	61.14	38.15	61.02	167.01	251,925	2.42%
Subtotal						1,285,412	12.34%
Other Foreign							
Toyota Group	58.60	19.83	37.16	58.56	75.32	144,591	1.39%
Geely Holding	69.87	16.93	52.48	69.85	95.80	87,335	0.84%
Stellantis	56.64	31.20	33.06	45.67	88.74	84,936	0.82%
Ford Group	65.17	26.45	51.14	61.20	88.64	61,407	0.59%
Renault-Nissan	28.84	9.60	20.61	25.98	42.50	57,169	0.55%
Tata Group	103.32	56.13	55.62	79.99	198.50	55,259	0.53%
GM	58.20	33.15	35.43	52.85	86.79	53,775	0.52%
Tesla	77.86	23.25	61.53	71.43	92.66	52,475	0.50%
Honda	44.24	9.28	34.83	44.11	57.83	36,898	0.35%
Subtotal						633,845	6.08%
Total	43.94	29.96	19.39	36.79	72.45	10,419,975	100%

consumers that its luxury vehicles' valuation can be on par with those from its German rivals.

Table 2 presents the summary statistics for used car prices from 2017 to 2024. Hyundai Motor Group leads the market with an average used car price of $9,090 for Hyundai and $9,240 for Kia, and a slightly higher average of $22,020 for its luxury brand Genesis. This dominance is reflected in their substantial market share, with Hyundai Motor Group accounting for 63.35% of all used car sales, indicating that their strong presence in the new car market has translated into dominance in the secondary car market.

German brands command higher average prices in the used car market. Mercedes-Benz leads with an average price of $31,160, followed by BMW at $21,490 and Volkswagen at $19,880. These brands collectively hold a 12.12% share of the used car market, reflecting their strong brand equity and sustained demand among used car consumers. Domestic brands such as GM Korea, Renault Korea, and KG Mobility have lower average used car prices, ranging from $4,710 to $8,440, and

Table 2. Used Car Prices and Market Shares by Manufacturers (2017-2024)

	Used Car Prices (Unit: ′000$)					Sales	
	Mean	**SD**	**p10**	**p50**	**p90**	**Count**	**Share**
Hyundai Motor Group							
Hyundai	9.09	8.53	1.01	6.61	20.50	4,955,122	30.56%
Kia	9.24	8.63	1.02	6.50	21.36	4,733,955	29.20%
Genesis	22.02	15.76	3.99	20.45	42.91	580,973	3.58%
Subtotal						10,270,050	63.35%
Domestic							
GM Korea	4.71	4.42	1.00	3.36	10.10	1,442,631	8.90%
Renault Korea	5.61	5.98	0.99	3.12	14.79	1,087,034	6.71%
KG Mobility	8.44	6.62	1.01	7.63	16.48	537,309	3.31%
Subtotal						3,066,974	18.92%
Germany							
BMW Group	21.49	17.44	3.86	18.24	42.22	752,462	4.64%
Mercedes-Benz	31.16	23.79	6.59	26.55	59.33	652,618	4.03%
Volkswagen	19.88	21.87	2.83	13.61	41.72	560,309	3.46%
Subtotal						1,965,389	12.12%
Other Foreign							
Stellantis	17.08	16.41	2.03	12.69	36.92	175,750	1.08%
Renault-Nissan	9.16	6.55	2.18	8.09	16.95	166,206	1.03%
Tata Group	29.37	22.21	7.14	24.82	55.91	143,487	0.89%
Toyota Group	17.06	14.27	2.24	14.01	35.70	140,180	0.86%
Ford Group	18.19	13.30	2.88	16.28	35.40	108,792	0.67%
Geely Holding	21.86	18.82	1.98	16.98	49.01	53,087	0.33%
GM	21.07	15.84	5.13	18.23	38.66	59,653	0.37%
Honda	10.42	9.82	1.04	6.61	25.62	49,553	0.31%
Tesla	40.84	20.16	19.45	38.22	65.31	12,838	0.08%
Subtotal						909,546	5.61%
Total	11.30	12.92	1.01	7.15	26.07	16,211,959	100%

together account for 18.92% of the market. Other foreign brands, including those from the Toyota Group, Ford, and Stellantis, occupy smaller market shares, with prices varying widely depending on the brand.

Table 3 presents the resale value ratios of vehicles from various manufacturers across different ages—1 year, 5 years, and 10 years—revealing how well these vehicles retain their value over time. Overall, the data shows a consistent pattern of depreciation, with the resale value ratio decreasing as vehicles age, reflecting the typical market behavior where cars lose a significant portion of their value within the first few years of ownership.

At Age 1, the overall average resale value ratio is 0.8016, indicating that cars lose approximately 19.84% of their new car value. Hyundai Motor Group shows strong value retention, particularly in the earlier years. Hyundai and Kia maintain higher resale value ratios compared to Genesis, indicating that their more affordable models hold their value better over time. Despite their high

Table 3. Resale Value Ratio over Vehicle Ages by Brands

	Age 1			Age 5			Age 10		
Brand	**Mean**	**SD**	**Count**	**Mean**	**SD**	**Count**	**Mean**	**SD**	**Count**
Hyundai Motor Group									
Hyundai	0.8152	0.2449	54,069	0.4934	0.1757	337,732	0.2071	0.1045	194,978
Kia	0.8143	0.2483	61,406	0.4962	0.1593	380,265	0.2282	0.1123	200,266
Genesis	0.7974	0.2410	11,308	0.4333	0.1347	62,942	0.1706	0.0844	14,959
Subtotal			68.78%			68.37%			63.70%
Other Domestic									
GM Korea	0.7507	0.2220	8,016	0.4334	0.1418	64,543	0.1704	0.0866	82,833
KG Mobility	0.7487	0.1917	5,934	0.4664	0.1509	44,620	0.1440	0.0762	16,490
Renault Korea	0.7805	0.2390	11,940	0.4089	0.1382	48,655	0.1382	0.0691	41,084
Subtotal			14.04%			13.82%			21.80%
Germany									
BMW Group	0.7881	0.1954	8,151	0.4381	0.1342	52,425	0.1600	0.0773	28,634
Mercedes-Benz	0.7927	0.1909	8,425	0.4200	0.1370	60,057	0.1489	0.0737	16,086
Volkswagen	0.8035	0.1906	6,101	0.3914	0.1380	21,465	0.1395	0.0756	26,145
Subtotal			12.30%			11.73%			11.00%
Other Foreign									
Toyota Group	0.8095	0.2226	1,780	0.4136	0.1521	9,135	0.1728	0.0958	3,980
Geely Holding	0.8174	0.2239	368	0.4228	0.1546	3,473	0.1351	0.0713	813
Stellantis	0.7642	0.1779	1,522	0.3985	0.1488	10,515	0.1621	0.1264	4,566
Ford Group	0.7498	0.1761	975	0.3961	0.1323	9,230	0.1356	0.0829	3,262
Renault-Nissan	0.6966	0.2689	850	0.3682	0.1316	13,742	0.1445	0.0749	4,943
Tata Group	0.7253	0.1560	398	0.3568	0.1110	13,334	0.1560	0.0863	3,453
GM	0.7238	0.2071	936	0.3753	0.1203	7,280	0.1340	0.0615	324
Tesla	0.7889	0.2846	1,838	0.3500	0.1053	379	-	-	-
Honda	0.7562	0.1748	321	0.4343	0.1469	2,460	0.1693	0.1011	1,188
Subtotal			4.88%			6.09%			3.50%
Total	0.8016	0.2371	184,338	0.4681	0.1617	1,142,252	0.1940	0.1040	644,004

prices, German brands such as BMW, Mercedes-Benz, and Volkswagen also demonstrate solid value retention, particularly within the first year, though they, like all brands, see a marked decline in value by the ten-year mark.

In contrast, other domestic brands such as GM Korea, KG Mobility, and Renault Korea tend to lose their value more quickly, with lower resale value ratios in the earlier years. By Age 5, these brands exhibit significant depreciation, with GM Korea and Renault Korea retaining less than 44% of their original value. At Age 10, the depreciation is even more pronounced, but dispersion of depreciation rates across manufacturers is less pronounced than the earlier years. Similarly, certain foreign brands, such as Renault-Nissan and Tata Group, also experience rapid value loss. By Age 5, Renault-Nissan vehicles retain just 36.82% of their original value, and this drops to 14.45% by Age 10. Tata Group shows a similar trend, with its vehicles retaining only 35.68% of their value by Age 5 and 15.60% by Age 10. These patterns highlight the correlation between faster depreciation rates and low market share for some brands compared to others, particularly when used vehicles are quite young.

5 Empirical Analysis

5.1 Are Consumers in the Automotive Market Myopic or Forward-Looking?

Before analyzing Hyundai's strategic use of price premiums in the secondary market, it is important to ascertain whether automobile consumers are rationally forward-looking by considering the future resale value of their vehicles when making new car purchasing decisions. If consumers are myopic, the resale value would not factor into their decision-making and should therefore not be considered as manufacturers' strategic variables of interest. To assess this, I employ a simple reduced-form demand model to estimate consumers' willingness to pay for vehicles with different depreciation rates, using data from the pre-entry period, specifically April 2017 to September 2023. This timeframe is particularly chosen to mark a period when Hyundai was unable to manipulate the resale value of their vehicles through buyback programs, thereby allowing us to explore whether manufacturers have an intrinsic motivation to enhance resale value in the post-entry period. The underlying assumption is that consumers form their expectations about the resale value of their cars based on (i) the initial price they paid for the new car and (ii) the car's expected depreciation rate, as outlined in the following equation:

$$\mathbb{E}[w_{j,t+\tau}] = \mathbb{E}[w^{\tau}_{j,t}] = \mathbb{E}[p_{j,t} \times f(\delta_j)] \equiv \mathbb{E}[p_{j,t}(1-\delta^1_j)(1-\delta^{\text{rest}}_j)^{\tau-1}] \tag{1}$$

$w_{j,t+\tau}$ denotes the wholesale price (i.e., resale value) of a used car model j of age τ purchased at time t. The age of a vehicle τ is measured in whole numbers, where $\tau = 1$ indicates that the car was sold (more specifically, registered, in my data) within 12 months of its initial registration by a new car owner. Similarly, $\tau = 2$ means that the used car was transacted within 13 to 24 months of its initial registration, and so forth. Given that my data spans eight years from 2017 to 2024, I am unable to observe the ages of used cars beyond this eight-year window. Therefore, I assume that consumers anticipate the ***future*** resale price of their vehicles by observing the prices of ***past*** model years of the same model in the ***current*** market. For instance, when a consumer purchases a new Honda Civic 2024 model and anticipates selling it after three years, she does not attempt to prophesy the future price of the 2024 model in 2027. Instead, she looks at the current market price of the **Civic 2021 model** and uses the price difference between 2021 and 2024 to estimate how much they can recoup in 2027. This logic is captured in the first equal sign in Equation 1, $\mathbb{E}[w_{j,t+\tau}] = \mathbb{E}[w^{\tau}_{j,t}]$, where consumers do not speculate on the future price by adding τ to the purchasing time as $w_{j,t+\tau}$, but rather base their expectations on the observed price of the same model j at the current time t, adjusted for the model's age τ, represented as $\mathbb{E}[w^{\tau}_{j,t}]$.

The remaining value of a vehicle after τ years is modeled as a multiplicative factor of the initial new car price $p_{j,t}$ and a function of the intrinsic depreciation rate of model j, δ_j, expressed as $\mathbb{E}[w^{\tau}_{j,t}] = \mathbb{E}[p_{j,t} \times f(\delta_j)]$. I define this depreciation rate as being decomposed into the first-year depreciation rate δ^1_j, which captures the significant loss in value immediately after purchase, and the average depreciation rate for the rest of subsequent years δ^{rest}_j. Suppose a vehicle's new car price is initially priced at $10,000. The resale values at different ages are as follows: $6,000 at age 1, $4,000 at age 2, $3,000 at age 3, and $2,500 at age 4. In this context, the first-year depreciation rate δ^1_j is defined as the drop ratio from $10,000 to $6,000, which equates to a 40% depreciation rate. For subsequent years, the depreciation rates are 33%, 25%, and 17%, respectively. The average depreciation rate beyond the first year, δ^{rest}_j, is calculated as the average of these rates. For example, when computing the resale value at age $\tau = 3$ $w^3_{j,t}$, it is calculated as:

$$w^3_{j,t} = 10,000(1 - 0.40)(1 - 0.29)^2 = 3,010.417 \approx 3,000$$

Similarly, the resale value of age $\tau = 4$ is $w^4_{j,t} = 10,000(1 - 0.40)(1 - 0.25)^3 = 2,531.25 \approx 2,500$. This average rate captures the compounded depreciation over these periods, reflecting the average loss to ages beyond the first year.

To make our model more tractable, I obtain the depreciation rate of a vehicle model j regardless of the time t it was purchased. This assumes that there exists intrinsic depreciation rate of model j that does not change over time. To estimate the first-year depreciation rate and the subsequent average depreciation rate for each model j in my granular dataset, I use the following linear projection:

$$log(w^{\tau}_{j(i)}) - log(p_{j(i)}) = \hat{\beta}_{j1} + (\tau - 1)\hat{\beta}_{j2} \tag{2}$$

The coefficient of interest is model j level depreciation rate δ^1_j and δ^{rest}_j but the raw data used to estimate this coefficient is each car i level, which represented as $j(i)$. $w_{j(i),\tau}$ is a wholesale price of a car model j of age τ and $p_{j(i)}$ is the price of the new car i when it was purchased from the manufacturer. This regression form comes from the transformation of Equation 1 where $w^{\tau}_j = p_j(1 -$

$\delta_j^1)(1-\delta_j^{\text{rest}})^{\tau-1} \Longrightarrow \frac{w_j^\tau}{p_j} = (1-\delta_j^1)(1-\delta_j^{\text{rest}})^{\tau-1} \Longrightarrow log(\frac{w_{j(i)}^\tau}{p_{j(i)}}) = log(1-\hat{\delta}_j^1) + (\tau-1)log(1-\hat{\delta}_j^{\text{rest}})$. This gets to $\hat{\beta}_{j1} = log(1-\hat{\delta}_j^1)$ and $\hat{\beta}_{j2} = log(1-\hat{\delta}_j^{\text{rest}})$ where $\hat{\delta}_j^1$ is predicted *ex-ante* depreciation rate of a model j at the first year and $\hat{\delta}_j^{rest}$ is predicted *ex-ante* depreciation rate of a model j after the first year.

I take the log to take into account the fact that the depreciation of a vehicle occurs the most in the first year and gradually decreases as it gets aged, which has a negative log form of value change over time. $\tau - 1 = [0, 1, 2, 3, \dots]'$ is a column vector which indicates the age minus one of a car.[16] Estimating Equation 2 provides $\hat{\beta}_{j,1}$ and $\hat{\beta}_{j,2}$, where $\hat{\beta}_{j,1}$ is a log-averaged *ex-ante* depreciation rate of a model j at the first year, and $\hat{\beta}_{j,2}$ is a log-averaged *ex-ante* depreciation rate of a model j after the first year. After estimating the predicted value, I exponentiate the term and obtain two $\hat{\delta}$ as:

$$\begin{aligned} \hat{\beta}_{j1} = &\quad log(1-\hat{\delta}_j^1) &\Longrightarrow &\quad \hat{\delta}_j^1 = 1 - exp(\hat{\beta}_{j1}) \\ \hat{\beta}_{j2} = &\quad log(1-\hat{\delta}_j^{\text{rest}}) &\Longrightarrow &\quad \hat{\delta}_j^{\text{rest}} = 1 - exp(\hat{\beta}_{j2}) \end{aligned}$$

Next, I estimate the reduced-form demand model putting these two depreciation rates into the linear demand model. I constrain the data only to include new cars for estimating the following Equation 3:

$$\begin{aligned} log(q_{j,t}) &= \alpha_1 - \alpha_2 p_{j,t} + X_{j,t}\Gamma + \sigma_t \\ &\quad + \underbrace{\alpha_3\hat{\delta}_j^1 + \alpha_4\hat{\delta}_j^{rest} + \tilde{\lambda}_j}_{\lambda_j} + \varepsilon_{j,t} \end{aligned} \tag{3}$$

$q_{j,t}$ is a new car quantity demanded for a model j at time t, and $p_{j,t}$ is a new car price for a model j at time t. $X_{j,t}$ is a (row) vector that represents the vehicle characteristics including size, fuel type, model year, and cc, and σ_t is a time fixed effects. One thing to note is that, as the additional characteristic of depreciation is estimated by the variation *across* different car model j, they will be absorbed by the model fixed effect λ_j. Therefore, I first estimate equation Equation 3 including the model fixed effect λ_j, then take out the model fixed coefficients, and regress these coefficients on the depreciation rate of the first year and the rest of the year to obtain $\hat{\alpha}_3$ and $\hat{\alpha}_4$. Furthermore, to address the potential endogeneity of the price variable, I instrument for new car prices using the quarterly

[16] Taking minus one is important because if not, then $\hat{\beta}_{j,2}$ would absorb some portion of the first-year depreciation, and underestimate the magnitude of $\beta_{j,1}$.

import prices of cold-rolled steel, hot-rolled steel, and the prices of other vehicles produced by the same manufacturer in different markets.

Table 4 shows the descriptive statistics for various variables at the vehicle model-month level to estimate Equation 3, based on a dataset of 5,948 observations forming an unbalanced panel. It highlights key characteristics of the South Korean automotive market, particularly focusing on depreciation rates, and dominance of gasoline luxury brand models. The average logged quantity demanded, represented as $\log(q_{jt})$, is 5.547 with a standard deviation of 2.236, indicating considerable variability in demand across different models and months. In terms of the actual quantity (q_{jt}), the average is 1,533 vehicles sold per month, showing a robust demand with a wide spread, as seen in the high standard deviation of 3,265. The top ten percent of the model-level demand reaches 4,734 observations, highlighting a skewed market where some models are significantly more popular. The average price of a new car (p_{jt}) is approximately $62,020, with prices generally ranging from $25,800 to $117,170 across the middle 80 percent of observations. Depreciation rates were estimated in the second stage of a regression model and 388 vehicle models available during the pre-period of this study. The average depreciation rate in the first year (δ_j^1) is 23.20%, which aligns well with the U.S. market . It is widely recognized that vehicles (and most durable goods) lose most of their value upon purchase, and this rate is consistent with both domestic and international studies, including those focusing on the U.S. market, where three-year depreciation rates range between 30% to 35% (Rush et al., 2022).[17] This suggests that the South Korean market's depreciation dynamics are similar to global patterns, although regional preferences and market conditions might slightly adjust these figures. In comparison, the average depreciation rate for the remaining years (δ_j^{rest}) is at 10.93%, reflecting the typical trend where vehicles stabilize in value after the initial steep decline.

The comparison of vehicle prices by fuel type reveals an interesting pattern. Hybrid cars are the most expensive on average at $65,300, followed by gasoline vehicles at $62,930, diesel at $59,620, and electric vehicles (EVs) at $55,640. This pricing hierarchy is somewhat counterintuitive because electric vehicles, generally associated with higher upfront costs due to advanced technology, are priced lower than expected. This trend may reflect the unique characteristics of the South Korean market, where luxury gasoline models are more prevalent, and hybrid technology is particularly popular. The scarcity of luxury EV models, along with a strong domestic market for hybrids, skews the over-

[17] Rush et al. (2022) do not report the annual depreciation rate of vehicle; instead, they aggregate the data and report it in three-year old intervals.

Table 4. Descriptive Statistics for Aggregated Data

Variable	**Mean**	**SD**	**p10**	**p50**	**p90**	**Count**
$log(q_{jt})$: Log quantity demanded	5.547	2.236	2.565	5.694	8.463	5,948
q_{jt}: Quantity demanded	1,533	3,265	13	297	4,734	5,948
p_{jt}: Price ($'000\$$)	62.02	40.64	25.80	49.91	117.17	5,948
Depreciation rate						
δ_j^1: Dep. rate in first year	0.2320	0.1219	0.0734	0.2394	0.3737	388
δ_j^{rest}: Dep. rate in rest years	0.1093	0.0544	0.0384	0.1123	0.1738	388
Price by fuel type						
-Diesel	59.62	32.61	27.24	49.51	110.23	1,701
-EV	55.64	20.52	31.93	54.71	83.76	222
-Gasoline	62.93	45.91	23.46	49.60	130.67	3,252
-Hybrid	65.30	36.67	31.29	49.61	115.79	773
Size (m^3)	13.80	2.47	11.08	13.53	17.21	5,948
Displacement (cm^3)	22.19	8.88	14.97	19.98	33.42	5,948

Note: This table presents descriptive statistics for the variables used in the analysis. The variables include the log of quantity sold ($log(q_{jt})$), price (p_{jt}), size, engine displacement capacity, and two depreciation variables (δ^1 and δ^{rest}). The statistics shown are the mean, standard deviation (SD), 10th percentile (p10), median (p50), 90th percentile (p90), and the count of observations (N).

all pricing landscape, making hybrids and gasoline vehicles appear costlier on average than EVs. Other vehicle characteristics include size, measured in cubic meters, with an average of 13.80 and most models ranging between 11.08 and 17.21 cubic meters. Displacement, another critical attribute influencing vehicle performance and fuel efficiency, averages 22.19 cubic centimeters, demonstrating a broad variety in vehicle offerings.

Table 5 presents estimates for the demand model of new vehicles, illustrating key relationships between pricing, product characteristics, and consumer behavior in the South Korean automotive market. The table reveals that depreciation rates are significantly important factor that affect consumer demand. The table shows the price coefficient is significantly negative across all specifications, indicating the disutility consumers experience with higher prices. Specifically, column (3) highlights that a \$1,000 increase in the price of a new car leads to a 2.76% decrease in quantity demanded.

Product characteristics play significant roles in shaping demand. Larger vehicles are positively associated with positive market demand, but displacement, which generally relates to engine size and power, does not show a strong positive relationship. Fuel type preferences further illustrate specific consumer inclinations, as shown in Table 4. Gasoline and hybrid vehicles are particularly favored, aligning with earlier observations of the market where luxury attributes are often linked

Table 5. IV Regression Results for Resale Value Effects

	(1)	(2)	(3)
		Dependent Variable: $log(q_{jt})$	
p_{jt} : Price ('000$)	-0.0307***	-0.0318***	-0.0276***
	(0.0054)	(0.0053)	(0.0049)
δ_j^1: Dep. Rate in first year	-2.064***	-2.190**	-1.176**
	(0.786)	(0.848)	(0.531)
δ_j^{rest}: Dep. Rate in rest years	-3.834***	-4.715***	-3.039***
	(1.390)	(1.500)	(0.939)
Size	0.270***	0.247***	0.233***
	(0.044)	(0.045)	(0.045)
Displacement	-0.015	-0.004	-0.001
	(0.021)	(0.022)	(0.019)
Fuel Type			
(Baseline: Diesel)			
Electronic	0.113	0.093	0.434
	(0.373)	(0.348)	(0.310)
Gasoline	0.606***	0.467***	0.531***
	(0.162)	(0.166)	(0.159)
Hybrid	0.963***	0.698***	0.697***
	(0.238)	(0.246)	(0.222)
Fixed Effects			
Model	✓	✓	✓
Model Year		✓	✓
Quarter			✓
Observations (model-quarter)	5,948	5,948	5,948
Num. of Models	388	388	388
R-sq	0.148	0.164	0.356
adj. R-sq	0.147	0.162	0.352

Note: Regressions are at the model-quarter level and standard errors are clustered at the model level. The dependent variable is the log of quantity sold for a vehicle model j in quarter t. Asterisks represent significance level at $1\%^{(***)}$, $5\%^{(**)}$, and $10\%^{(*)}$.

to these fuel types. This is especially interesting as electric vehicles (EVs), usually expected to be preferred holding other characteristics constant, do not command the same premium in this market.

The depreciation rate variables provide valuable insights into consumer willingness to pay based on expected future vehicle values. The first-year depreciation rate (δ_j^1) shows a consistent disutility for higher depreciating models, which holds across different model specifications. Using column (3) as a reference, the calculation $dp_{jt}/d\delta_j^1 = -1.176/0.0276 = -\$42,608$ suggests that in an extreme scenario where the first-year depreciation rate shifts from 0% to 100% (i.e., the vehicle completely loses its whole resale value within 12 months of purchase), consumers' willing to pay decreases by $42,608 for that vehicle model. More practically, if an automotive manufacturer can reduce its first-year depreciation rate by 10%, consumers are willing to pay $4,260 more, reflecting how crucial the resale value is to new car purchasing decisions. The depreciation rate for subsequent years (δ_j^{rest}) shows even more significant consumer sensitivity. Consumers would theoretically pay $110,108 more if a vehicle had no depreciation (100% to 0%) over its subsequent years, translating into a willingness to pay $11,010 more if a car's depreciation is reduced by 10% on average for all years after the first. This highlights that long-term value retention is also an essential factor for consumers, emphasizing their forward-looking behavior.

The overall results suggest that resale value is a critical aspect of consumer decision-making in the automotive market. Manufacturers might have an incentive to consider the resale value of their products since it can influence initial purchase prices and demand. Manufacturers can enhance their vehicles' appeal in a market where consumers are clearly attentive to both initial and future costs.

5.2 Exploring the Relationship Between Resale Value and Used Car Circulation

This section tests if the resale value of vehicle is correlated with strong or weak used car sales. For instance, if the initial price of a vehicle is set too high relative to its perceived value, it may undergo a substantial price drop in the secondary market. Used car buyers often anticipate this drop and wait for the price to fall, resulting in high demand and circulation rate because of the vehicle's low resale value. In this case, low value does not indicate weak demand; rather, low resale value ratio reflects strategic consumer behavior that increases transaction frequency. On the other hand, strong demand in the secondary market may correspond with high resale values. Vehicles that maintain their value due to quality, brand reputation, and durability often have high turnover in the secondhand market. The high resale value attracts buyers, even as the vehicles age, suggesting that strong secondary market activity is associated with desirable attributes of the vehicle. Understanding this relationship verifies the theoretical prediction of which cars Hyundai has an incentive to provide.

To evaluate which one of contrasting scenarios best explains this market, I define two key measures: the used prevalence ratio (UPR) and the resale value ratio (RVR). I adopt the used prevalence ratio (UPR) used in Bognar et al. (2023) to gauge the used car circulation compared to total registered new cars. I define $UPR_{j,y,f}$ of a given model (j) - model year (y) - fuel type (f) combination as follows:

$$UPR_{j,y,f} = \frac{Used_{j,y,f}}{New_{j,y,f}}$$

where $Used_{j,y,f}$ is the *total* number of used car transactions of model j of model year y with fuel type f during the pre-period from April 2017 to September 2023. $New_{j,y,f}$ is the *total* number of new registrations for model j of model year y with fuel type f that ever existed during the pre-period from April 2017 to September 2023. Thus, $UPR_{j,y,f}$ measures the percentage of new vehicles of a given product ever circulated within the used car market during the sample period. I define the resale value ratio (RVR) of a given model (j) - model year (y) - fuel type (f) combination, only for the first-year old vehicles, dividing the resale value of the first-year old car by the total cost of buying the new car. RVR captures the value retention of a vehicle by comparing its first-year resale value to its initial purchase price. As shown in Table 4, the first-year depreciation is the most crucial in value loss after the first purchase, so I only used the first-year resale value ratio of a vehicle, not the subsequent years. I regress $UPR_{j,y,f}$ on the first-year $RVR_{j,y,f}$ and other controls to test if the resale value ratio is positively or negatively correlated with the used prevalence ratio.

Some important descriptive statistics for the used prevalence ratio (UPR) across model years and the first-year resale value ratio (RVR) by automotive brands are shown in Table 6. The UPR, which measures the frequency of used car circulation compared to new car circulation, shows an average value of 47.1%. This suggests that, on average, approximately half of the new cars sold during the 7-year period eventually entered the secondary market. The UPR is strongly correlated with the age of the vehicle: for 2017 models, the UPR is 94.8%, indicating that nearly all vehicles from that model year have been sold at least once in the used market. As expected, the ratio decreases for more recent model years, reflecting the shorter time they have had to circulate; the UPR is 73.2% for 2018 models, 45.5% for 2019, 28.6% for 2020, and continues to decline with more recent models.

The first-year resale value ratio (RVR), which captures the proportion of the new car price retained after one year, has an average of 79.7%. This aligns with the previously noted average depreciation rate of 23%, derived from a logarithmic transformation. However, there is significant variation in RVR across different car brands, reflecting diverse depreciation rates and resale values.

Hyundai leads the market with an RVR of 83.7%, showing that their vehicles retain the highest proportion of their original value after the first year among all brands. Kia follows closely with an RVR of 81.7%, further cementing the strong market position of the Hyundai Motor Group in terms of maintaining vehicle value. Interestingly, although German brands of Mercedes-Benz, BMW, and Volkswagen are the most expensive luxury vehicle groups in terms of car prices, their first-year depreciation rates are not the lowest. Mercedes-Benz, for example, has an RVR of 81.1%, BMW shows 80.6%, and Volkswagen has 81.9%. This indicates that higher new car prices do not necessarily equate to lower depreciation rates. Other intrinsic factors, such as the perceived durability, brand

Table 6. **Used Circulation Rate (UPR) and First-Year Resale Value Ratio (RVR)**

	Mean	SD	p10	Median	p90	Count
UPR	0.471	0.480	0.033	0.348	1.035	1,355
2017	0.948	0.537	0.495	0.867	1.462	281
2018	0.732	0.377	0.367	0.652	1.168	240
2019	0.455	0.266	0.251	0.385	0.715	207
2020	0.286	0.161	0.161	0.254	0.422	195
2021	0.178	0.377	0.066	0.119	0.246	183
2022	0.076	0.181	0.020	0.041	0.109	155
2023	0.016	0.027	0.002	0.008	0.039	94
First-year RVR	0.797	0.114	0.688	0.798	0.906	1,355
Hyundai Group						
Hyundai	0.837	0.139	0.714	0.838	0.969	169
Kia	0.817	0.118	0.709	0.824	0.933	195
Genesis	0.793	0.095	0.699	0.799	0.886	54
Other Domestic Brands						
GM_Korea	0.775	0.156	0.636	0.764	0.868	46
KG_Mobility	0.750	0.068	0.678	0.744	0.823	42
Renault_Korea	0.698	0.135	0.527	0.726	0.836	36
Germany brands						
Mercedes-Benz	0.811	0.062	0.744	0.807	0.881	142
BMW_Group	0.806	0.126	0.714	0.801	0.896	254
Volkswagen	0.819	0.068	0.754	0.822	0.900	107
Other Foreign						
Geely_Holding	0.831	0.068	0.738	0.826	0.896	27
Tesla	0.804	0.078	0.673	0.831	0.911	8
Honda	0.797	0.062	0.716	0.793	0.877	27
Toyota_Group	0.778	0.079	0.684	0.789	0.876	54
Tata-Group	0.755	0.042	0.712	0.749	0.807	32
Stellantis	0.740	0.073	0.637	0.747	0.827	62
Ford_Group	0.727	0.124	0.640	0.732	0.829	44
GM	0.717	0.091	0.575	0.731	0.806	38
Renault_Nissan	0.673	0.146	0.317	0.709	0.812	18

Note: Table shows summary statistics for UPR and RVR for 1,355 model-model year-fuel type level observations, including the mean, standard deviation (SD), 10th percentile (p10), median (p50), 90th percentile (p90), and count of observations (count).

reputation, market demand, maintenance costs, and availability of replacement parts, likely play a crucial role in determining the resale value of these vehicles.

Regarding the other brands, Geely Holdings, which owns the Volvo brand, shows an RVR of 83.1%, despite their small market presence, reflecting its strong reputation and perceived quality in the South Korean market. Volvo's focus on safety, longevity, and robust design might contribute to this high resale value. In contrast, other domestic brands such as GM Korea, KG Mobility, and Renault Korea exhibit significantly lower RVRs, ranging from 69.8% to 77.5%. This low retention of value may be linked to their small market share in the primary market, less consumer confidence, and perhaps mediocre investment in brand image or vehicle quality compared to their competitors.

One important observation is that Genesis, Hyundai's luxury brand, depreciates a bit faster than the German luxury brands, with an RVR of 79.3%. Despite their competitive pricing, which averages $20,000 less than comparable German models, Genesis vehicles tend to lose their value more quickly. This could be due to a combination of factors such as brand perception, market positioning, or perhaps the relative novelty of Genesis in the luxury vehicle segment compared to well-established German brands. This faster depreciation might incentivize Hyundai to strategically intervene in the resale market, aiming to strengthen their competitiveness in the luxury segment.

These findings suggest that depreciation rates are influenced by more than just the initial price of the car. Factors such as brand reputation, consumer perceptions of quality and durability, after-sales service, and the overall desirability of the vehicle in the secondary market play crucial roles. Brands that successfully maintain high resale values often enjoy stronger demand in the used car market, which reinforces their market presence and brand loyalty in the primary market. Conversely, brands with lower resale values may struggle to retain customer loyalty and face greater challenges in maintaining their competitive edge. Understanding these nuanced market dynamics is essential for manufacturers as they strategize to enhance both their primary and secondary market performance.

Table 7 presents the results of regression analyses examining the relationship between the used prevalence ratio (UPR) and the first-year resale value ratio (RVR), along with model year and other fixed effects. The three columns represent different specifications, progressively incorporating more fixed effects: column (1) includes no fixed effects, column (2) adds model fixed effects, and column (3) includes both model and fuel type fixed effects.

The key coefficient of interest between the first-year RVR and UPR is positive and statistically significant across all specifications, with coefficients ranging from 0.291 in column (1) to 0.388 in column (3). This indicates that higher retained value of vehicles is associated with greater circulation of those vehicles in the used car market. Specifically, based on the coefficient of 0.388 in column (3), a vehicle's first-year value increasing from 0% to 100% can lead to a 38.8% increase in circulation in the secondary market. This positive correlation suggests that higher resale values do not deter but rather are associated with the higher frequency of used car transactions, supporting the hypothesis that stronger demand in the used car market is tied to high retained value rather than solely low prices, affirming the second explanation previously discussed.

The results for model year variables consistently show a negative relationship with UPR, which aligns with earlier summary statistics. Using 2017 as the baseline, the coefficients for subsequent model years progressively decrease, reflecting the expected pattern: newer models have had less

Table 7. Relationship Between UPR and RVR

	(1)	(2)	(3)
First-year RVR	0.291***	0.380***	0.388***
	(0.091)	(0.093)	(0.093)
Model Year			
(Baseline: 2017)			
2018	-0.219***	-0.257***	-0.254***
	(0.031)	(0.023)	(0.023)
2019	-0.515***	-0.518***	-0.512***
	(0.033)	(0.026)	(0.026)
2020	-0.692***	-0.702***	-0.693***
	(0.034)	(0.027)	(0.027)
2021	-0.797***	-0.797***	-0.785***
	(0.034)	(0.028)	(0.028)
2022	-0.905***	-0.914***	-0.899***
	(0.036)	(0.030)	(0.030)
2023	-0.968***	-0.946***	-0.928***
	(0.043)	(0.034)	(0.035)
Fixed Effects			
Fuel Type			✓
Model		✓	✓
N	1,355	1,355	1,355
Num. of Models	377	377	377
Num. of Fuel Type	4	4	4
R-sq	0.474	0.823	0.825
adj. R-sq	0.471	0.754	0.755

Note: This table presents the regression results for different models. The dependent variable is the used ratio. Standard errors are in parentheses. Asterisks represent significance levels at $1\%^{(***)}$, $5\%^{(**)}$, and $10\%^{(*)}$.

time to circulate in the used car market, and thus their UPR values are lower. For instance, the coefficient for the 2018 model year is -0.254 in column (3), indicating that 2018 vehicles circulate less frequently in the used market compared to 2017 models, with the magnitude of this effect increasing (in absolute terms) for more recent model years. The decline continues sharply, reaching -0.928 for the 2023 model year, confirming that the age of the vehicle plays a significant role in its likelihood of appearing in the used car market. The inclusion of fixed effects progressively improves the model fit, as evidenced by the increase in the R-squared values from 0.474 in column (1) to 0.825 in column (3). The findings collectively reinforce the notion that high resale value correlates with strong used car market activity, challenging the simplistic view that lower value always drives higher circulation and highlighting the multifaceted nature of consumer demand in the secondary market.

5.3 The Role of Ex-Ante Depreciation Rates on Trade-In Premiums in Hyundai's Pricing Decisions

The pivotal role of *ex-ante* depreciation rates in shaping Hyundai's trade-in strategy underscores a key aspect of the company's approach to enhancing resale values. Prior to Hyundai's entry into the secondary car market, certain vehicle models experienced sharp value declines in their first year of ownership (see subsection 5.2), and rational consumers factor the resale value into the current purchasing decisions (see subsection 5.1). Recognizing this, Hyundai Motor Group has an incentive to develop a strategic response by adjusting its trade-in premiums to account for these disparities. In this section, I quantify how these depreciation rates influence the premiums offered by Hyundai. This targeted approach reveals how Hyundai systematically leverages trade-in premiums to offset early value losses, fostering stronger resale values and positioning itself more competitively in the primary market. To verify this impact, I estimate the following regression model using the wholesale data on vehicles purchased by Hyundai Motor Group from October 2023 to March 2024:

$$\begin{aligned} w_{it}^{H} - w_{j(i)t}^{D} = \beta \left(1 - \hat{\delta}_{j(i)}^{1}\right) &+ \underbrace{Size_{j(i)t} + CC_{j(i)t} + Weight_{j(i)t} + Fuel_{j(i)t}}_{X'_{j(i)t}} \\ &+ \underbrace{Mile_{it} + Age_{it} + 1(\text{Gender}) \times 1(\text{Age}) \times 1(\text{Firm})}_{W'_{it}} + \tau_t + \varepsilon_{it} \end{aligned} \tag{4}$$

The dependent variable, $w_{it}^{H} - w_{j(i)t}^{D}$, represents Hyundai's trade-in premium, defined as the difference between the trade-in price of a used car i paid by Hyundai at month t (w_{it}^{H}) and the average wholesale price of the same model-fuel j paid by independent dealers at the same month ($w_{j(i)t}^{D}$). The variable of interest is the *ex-ante* first-year depreciation rate ($\hat{\delta}_{j(i)}^{1}$), which reflects the value loss of the vehicle within the first year of its purchase *before* Hyundai could influence the resale value of its products. To define $\hat{\delta}_{j(i)}^{1}$, data from the six years prior to Hyundai's entry into the market was used, calculating the average first-year depreciation rate for each model-fuel combination (j). This rate represents the average value loss observed for model-fuel j, which is then matched with the same model-fuel's trade-in premiums (w_{it}^{H}) in the analysis.

The coefficient of interest, β, captures the effect of the first-year depreciation rate on the trade-in premium. Model-fuel-specific characteristics ($X'_{j(i)t}$) include vehicle size ($Size_{j(i)t}$), engine displacement in cubic centimeters ($CC_{j(i)t}$), vehicle weight ($Weight_{j(i)t}$), and fuel type ($Fuel_{j(i)t}$). Car-specific characteristics (W'_{it}) encompass the odometer reading in miles ($Mile_{it}$), vehicle age in years (Age_{it}), and demographic variables, including gender, age, and firm status, represented by the interaction term $1(\text{Gender}) \times 1(\text{Age}) \times 1(\text{Firm})$. Month fixed effects ($\tau_t$) account for time-specific influences that uniformly affect all vehicles in a given period, while the error term (ε_{it}) is clustered at the model-fuel level to adjust for unobserved shocks within specific vehicle groups. This empirical approach aims to estimate how Hyundai's trade-in premiums respond to the varying first-year depreciation rates across different vehicle models. The analysis tests the hypothesis that Hyundai strategically adjusts its premiums, offering higher payments for models that experience greater depreciation in their first year. Examining the variation in premiums based on these depreciation rates provides evidence of Hyundai's targeted strategy in the secondary market.

The summary statistics in Table 8 provides an overview of the key variables used in examining the impact of depreciation rates on Hyundai's trade-in premiums. The main variable of interest, Hyundai's premium, is calculated as the difference between Hyundai's trade-in wholesale price and the average wholesale price offered by independent dealers for the same vehicle model. On average, Hyundai's premium is $3,206, indicating that Hyundai pays on average more than independent dealers to acquire used vehicles. However, this premium varies substantially, with the lower 10th percentile at $932 and the upper 90th percentile reaching as high as $9,667, highlighting the huge heterogeneity in Hyundai's trade-in pricing strategy across different vehicle conditions and models. The first-year resale value ratio, which reflects the proportion of a car's value retained after the first year, averages 81.6%. This aligns closely with subsection 5.2 regarding first-year depreciation rates, suggesting that about 20% of a vehicle's value is lost within the initial year of ownership. The spread of values, ranging from 74.7% at the 10th percentile to 92.4% at the 90th percentile, suggests significant variation in how well or bad different models retain their value. The table also includes vehicle characteristics such as odometer readings, vehicle age, engine displacement, weight, and size, all of which are relevant to understanding how Hyundai assesses the condition and potential resale value of the vehicles they purchase. The average odometer reading is approximately 22,700 miles, with a wide range from 7,460 miles at the 10th percentile to 42,880 miles at the 90th percentile. The average age of vehicles is 2.85 years, suggesting that Hyundai engages in trade-ins involving relatively new vehicles as per the government regulation. The vehicle characteristics such as engine displacement, weight, and size also provide the types of vehicles Hyundai targets. For instance, the average engine

Table 8. Descriptive Statistics for Trade-in Cars

	Mean	SD	p10	Median	p90	N
$w^H_{it} - w^D_{j(i)t}$: Hyundai's premium	3.206	3.439	0.932	2.999	9.667	2,742
$1 - \delta^1_j$: 1st-year retained value	0.816	0.060	0.747	0.801	0.924	2,742
Odometer ('000 mile)	22.70	13.45	7.46	19.89	42.88	2,742
Vehicle Age	2.85	1.12	1.83	2.67	4.17	2,742
Displacement (cm^3)	2,329	704	1,598	2,359	3,470	2,742
Weight (kg)	2,114	314	1,740	2,105	2,555	2,742
Size (m^3)	14.49	1.91	12.13	14.09	17.21	2,742

Table 9. The Impact of *ex-ante* Resale Value Ratio on Hyundai's Trade-in Premiums

	Dependent Variable: Hyundai's Trade-in Premium (= $w^H_{it} - w^D_{j(i)t}$) ('000\$)					
	(1)	(2)	(3)	(4)	(5)	(6)
$1 - \hat{\delta}^1_j$: 1^{st} year resale value ratio	-14.944***	-15.407***	-16.484***	-12.938***	-13.517***	-14.587***
	(5.223)	(4.884)	(5.151)	(4.490)	(4.279)	(4.467)
Odometer ('000 mile)	-0.122***	-0.133***	-0.120***	-0.109***	-0.122***	-0.107***
	(0.014)	(0.014)	(0.014)	(0.010)	(0.010)	(0.010)
Age	-1.953***	-1.897***	-1.954***	-1.685***	-1.627***	-1.681***
	(0.234)	(0.231)	(0.234)	(0.189)	(0.188)	(0.190)
Displacement (cm^3)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Weight (kg)	0.005***	0.005***	0.005***	0.005**	0.005**	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Size raw (m^3)	-0.780**	-0.716**	-0.736**	-0.689*	-0.624*	-0.648*
	(0.294)	(0.295)	(0.298)	(0.353)	(0.359)	(0.357)
Fuel type						
(Baseline: Diesel)						
EV	-6.262***	-6.196***	-6.312***	-5.495***	-5.458***	-5.614***
	(1.663)	(1.780)	(1.639)	(1.592)	(1.758)	(1.600)
Gasoline	0.709	0.735	0.639	0.837	0.886	0.790
	(0.600)	(0.656)	(0.620)	(0.651)	(0.711)	(0.668)
Hybrid	-0.968	-0.909	-1.067	-0.937	-0.864	-1.040
	(0.787)	(0.795)	(0.786)	(0.689)	(0.717)	(0.691)
Size Type						
(Baseline: Small)						
Large	7.176***	6.384***	7.023***	6.753***	5.863***	6.596***
	(1.440)	(1.502)	(1.458)	(1.390)	(1.462)	(1.399)
Medium	5.643***	5.044***	5.541***	5.035***	4.378***	4.936***
	(1.114)	(1.131)	(1.112)	(1.019)	(1.030)	(1.008)
Constant	17.500***	19.102***	20.425***	14.330***	16.385***	17.367***
	(4.262)	(3.649)	(4.177)	(3.262)	(2.947)	(3.279)
Fixed Effects						
Month		✓	✓		✓	✓
Demographics	✓		✓	✓		✓
Number of observations	2,742	2,742	2,742	2,688	2,688	2,688
R-sq	0.530	0.527	0.541	0.564	0.556	0.578
adj. R-sq	0.526	0.524	0.536	0.559	0.553	0.573

Note: Regressions are at the VIN level and standard errors are clustered at the model level. Asterisks represent significance level at $1\%^{(***)}$, $5\%^{(**)}$, and $10\%^{(*)}$.

displacement is 2,329 cm³, with substantial variability, indicating that Hyundai deals with a wide range of vehicles, from compact cars to larger, more powerful models.

Table 9 shows the results of estimating Equation 4. The dependent variable in all models is Hyundai's trade-in premium. The first three columns use the full sample of 2,742 observations, while the last three columns exclude the top 1% and bottom 1% of samples, narrowing the analysis to 2,688 observations. The specifications vary by the inclusion of fixed effects, which is individual demographics, month, or both. The first-year retained value ratio $(1 - \hat{\delta}_j^1)$ is the primary variable of interest, capturing the proportion of a car's value that remains after the first year. Based on column (3), which includes both month and demographic fixed effects, the coefficient is -16.484, significant at the 1% level. The result indicates that Hyundai offers a significantly less premium for vehicles that retain more of their value in the first year compared to those that depreciate rapidly. For example, if Model A completely loses its value in the first year (100% depreciation) while Model B retains all its value (0% depreciation), Hyundai would pay \$16,484 more for Model B than for Model A. This demonstrates Hyundai's strategic intervention in the secondary market, as they are willing to pay higher premiums for vehicles that depreciate fast, likely to increase the resale value of these models and attract more trade-ins from owners who see Hyundai as a better buyer. To further exemplify, if Model A and Model B have first-year depreciation rates of 25% and 15%, respectively, Hyundai would offer a \$1,648 higher premium for Model B, which depreciates slower. In practical terms, this behavior is reflected in the market: Hyundai offers almost no premium for a model like the Avante, which depreciates only 8% in the first year, while they provide around \$4,000 in premiums for luxury models like the G80, which depreciates faster. This strategic use of trade-in premiums allows Hyundai to adjust the resale value of their vehicles in the secondary market, enhancing their competitive position, particularly for higher-end models.

Other vehicle characteristics also influence Hyundai's trade-in premiums, which suggests there might be some sample selection from Hyundai. The odometer reading, measured in thousands of miles, is consistently negative and statistically significant across all specifications. In column (3), the coefficient of -0.120 implies that within the same model, Hyundai's trade-in premium decreases by approximately \$120 for every additional 1,000 miles on the odometer. This negative relationship is expected, as higher mileage indicates more usage and wear, reducing the vehicle's resale value. Hyundai, like other buyers, discounts the premium to account for the increased risk of maintenance issues and reduced remaining lifespan. The coefficient for vehicle age is also negative and significant, with a value of -1.954 in column (3). This suggests that for each additional year of vehicle age of the same model, Hyundai's trade-in premium decreases by about \$1,954. This decrease reflects the natural depreciation of vehicles over time, where older cars are less valuable due to outdated features, wear and tear, and lower desirability compared to newer models. Displacement, measured in cubic centimeters (cm^3), shows a consistently insignificant relationship with Hyundai's premium across all specifications. The coefficient on weight is positive and statistically significant, though relatively small, with a value of 0.005 in column (3). This positive relationship could be due to heavier vehicles often being perceived as more robust or safer, attributes that might command slightly higher incentive to pay premiums. The size of the vehicle, measured in cubic meters (m^3), has a negative coefficient of -0.736 in column (3), indicating that larger vehicles within the same size type (i.e., small, medium or large) are associated with a lower premium from Hyundai. Regarding fuel type, electric vehicles (EVs) have a consistently negative and highly significant coefficient, -6.312 in column (3), which shows that Hyundai offers around $6,312 less for EVs compared to the baseline category of diesel vehicles. This substantial discount likely reflects concerns about battery degradation, limited charging infrastructure, and uncertain resale value in the EV market, which may deter Hyundai from offering high premiums. Gasoline and hybrid vehicles do not show statistically significant differences from the baseline diesel category in terms of the premiums Hyundai offers. For size categories, the coefficient for large vehicles is positive and significant at 7.023 in column (3), suggesting that Hyundai pays about $7,023 more for large vehicles compared to compact cars. This premium could be due to the higher initial prices and perceived value of larger vehicle models, which may include SUVs or luxury sedans in the resale market. Similarly, medium-sized vehicles receive a premium of $5,541 over compact cars, according to column (3). This positive effect aligns with consumer preferences for medium-sized vehicles, which balance practicality and value, making them attractive in the secondary market.

In Table 9, the significant coefficients of covariates other than the first-year retained value suggest that factors beyond depreciation might be influencing Hyundai's decision to pay a premium. This raised the concern of sample selection bias, as Hyundai might be systematically targeting specific types of vehicles even after controlling the first-year retained value of that model. To quantify how much these additional factors contribute to the observed price gap and isolate the contribution of depreciation rate on premium, I use the Gelbach decomposition (Gelbach, 2016). This method, frequently applied in labor economics, is originally used to decompose wage premiums—such as the wage gap between men and women or between white and non-white workers—by distinguishing how much of the wage premium can be explained by various covariates like education, experience,

Table 10. Gelbach Decomposition - Baseline vs. Full Model

	Dep. Var.: Hyundai's Wholesale Price (= w^H_{it})		Contribution of changes in $w^D_{j(i)t}$	
	(1) Baseline Model	(2) Full Model	(3) Coefficients	(4) Percentage (%)
$w^D_{j(i)t}$: Dealer's wholesale price	1.142***	0.994***	-	-
	(0.042)	(0.030)	(-)	(-)
$1-\delta^1_j$: 1^{st} year retained value		-20.033***	0.0746***	50.40%
		(4.591)	(0.0014)	
Odometer ('000 mile)		-0.119***	0.0019***	1.26%
		(0.013)	(0.0002)	
Age		-2.019***	0.0095***	6.45%
		(0.227)	(0.0006)	
Displacement (cm^3)		0.000	0.0207***	13.98%
		(0.001)	(0.0013)	
Size raw (m^3)		-0.225	-	-
		(0.176)	(-)	(-)
N(Dealers$_j$)		2.140***	0.0179***	12.08%
		(0.706)	(0.0008)	
Q_j		-0.028*	0.0013***	0.90%
		(0.016)	(0.0003)	
Fuel Type (Baseline: Diesel)				
EV		-4.439***	0.0009	0.62%
		(1.413)	(0.0007)	
Gasoline		-0.019		
		(0.538)		
Hybrid		-1.798***		
		(0.648)		
Size Type (Baseline: Small)				
Large		7.776***	0.0210***	14.20%
		(1.486)	(0.0010)	
Medium		5.825***		
		(1.138)		
Fixed Effects				
Demographics		✓	0.0001	0.08%
			(0.0003)	
Month		✓	0.0000	0.02%
			(0.0001)	
Constant	-0.885	36.582***		
	(0.830)	(5.012)		
Number of observations	2,742	2,742		
R-squared	0.760	0.884		

Note: Regressions are at the VIN level and standard errors are clustered at the model level. Asterisks represent significance level at 1%$^{(***)}$, 5%$^{(**)}$, and 10%$^{(*)}$.

and occupation. In my case, the decomposition determines how much of Hyundai's premium over dealer prices is driven by factors such as first-year depreciation, odometer readings, vehicle age, and so on.

Table 10 shows the results of the Gelbach decomposition, which breaks down the factors contributing to the gap between Hyundai's wholesale price and the dealer's wholesale price. In column (1), the baseline model regresses Hyundai's wholesale price purely on the dealer's wholesale price and constant. The coefficient of 1.142 indicates that, on average, Hyundai pays approximately 14.2% more than dealers for the same vehicle. This 14.2% premium corresponds to the difference in Table 8, where Hyundai pays \$3,206 more on average than the dealer's price of \$22,577. This baseline model provides an initial look at the raw premium Hyundai offers without accounting for additional covariates. Column (2), the full model, introduces a range of control variables—such as the first-year retained value, odometer readings, and other vehicle characteristics—allowing us to understand what drives this price difference. After controlling for these variables, the coefficient for the dealer's wholesale price drops to 0.994, which suggests that, once adjusted for the covariates, Hyundai's price is almost identical to the dealer's wholesale price. This outcome implies that the control variables successfully capture most of the factors driving Hyundai's premium. The full model shows a premium gap of 14.8% (=1.142 - 0.994), slightly higher than the raw 14.2%.

Column (3) provides the raw coefficients estimated in the Gelbach decomposition, which helps break down the factors contributing to the 14.8% premium by Hyundai. Column (4) translates these raw coefficients into percentages, representing how much each variable contributes to the change in Hyundai's wholesale price relative to dealers'. The most striking finding is the first-year resale value ratio $(1 - \delta_j^1)$, which accounts for 50.40% of the explained difference, emphasizing that Hyundai's primary motivation for offering a premium is tied to the vehicle's depreciation in its first year. The fact that over half of the gap can be explained by this factor aligns with Hyundai's broader objective to support the resale value of its cars by paying more upfront for vehicles that are likely to lose value rapidly in the secondary market. Other variables, like displacement and size type, contribute less but still play significant roles in explaining the price gap, accounting for 13.98% and 14.20%, respectively. These contributions suggest that Hyundai's premium is also influenced by the vehicle's characteristics beyond depreciation. However, the much smaller contributions from variables like odometer readings (1.26%) and age (6.45%) indicate that these factors, while relevant, are secondary considerations compared to the impact of first-year depreciation. The positive contributions of variables such as displacement and size type, despite the overwhelming focus on depreciation, hint at a sample selection issue. Hyundai appears to select vehicles based not only on their depreciation profile but also on other characteristics, such as engine size or vehicle type, which may reflect a preference for certain types of vehicles that further explain their pricing strategy. Admitting this sample selection issue, it's clear that depreciation remains the key motivator behind Hyundai's premium, but other factors cannot be ignored.

Table 11 presents the contribution of different regressors to the price gap between Hyundai and

Table 11. Subsample Gelbach Decomposition

	Contribution of changes in $w^D_{j(i)t}$			
	Overall	Subsample		
		Genesis	*Hyundai*	*Kia*
$1-\delta^1_j$: 1^{st} year retained value	50.40%	96.07%	63.85%	45.69%
Odometer ('000 mile)	1.26%	0.56%	1.12%	1.28%
Age	6.45%	18.21%	3.85%	6.79%
Displacement (cm^3)	13.98%	-12.30%	12.67%	8.84%
N(Dealers$_j$)	12.08%	0.71%	-1.67%	11.99%
Q_j	0.90%	0.86%	3.76%	-3.01%
Fixed Effects				
Fuel Type	0.62%	-1.97%	2.37%	18.91%
Size	14.20%	1.20%	16.36%	6.24%
Demographics	0.08%	-3.73%	-2.68%	3.38%
Time	0.02%	0.39%	0.35%	-0.10%
Total	100.00%	100.00%	100.00%	100.00%

dealer wholesale prices, with a breakdown across subsamples: Genesis, Hyundai, and Kia. As seen in Table 10, the overall contribution of the first-year retained value ($1-\delta^1_j$) is 50.40%, making it the dominant factor explaining Hyundai's premium over dealers. In the Genesis subsample, the first-year retained value explains an overwhelming 96.07% of the price difference. This highlights that depreciation is nearly the sole driver behind Hyundai's decision to offer higher premiums for Genesis vehicles, as their first-year depreciation rate is relatively higher compared to other German luxury brands. For Hyundai brand, the retained value contributes 63.85% to the price difference, while other factors like displacement and size type also play a role. This shows that Hyundai considers a broader range of characteristics in its pricing strategy for its core brand. In the Kia subsample, the first-year retained value accounts for 45.69% of the price gap. While depreciation is still important, other factors, such as fuel type and displacement, have a stronger influence, reflecting Kia's focus on more practical vehicle attributes.

5.4 The Impact of Hyundai's Secondary Market Entry on Primary Market

Table 12 presents the regression results examining the impact of Hyundai's entry into the secondary market in October 2023 on new car prices using a difference-in-difference (DID) method. The dependent variable across all models is the new car price (p_{it}). The analysis is conducted at the vehicle identification number (VIN) level, providing a substantial number of observations: over 1.7 million for the full sample, 1.5 million for domestic brands, and 1.3 million for Hyundai vehicles alone. The sample period for analyzing the price change spans 12 months, with six months prior to Hyundai's

Table 12. Changes in New Car Prices across Hyundai Brands

	Dependent Variable: p_{it} ('000\$)					
Sample	Full	Domestic	Hyundai	Full	Domestic	Hyundai
	(1)	(2)	(3)	(4)	(5)	(6)
Post×Hyundai Motor Group	-1.699	0.467	0.619			
	(1.159)	(0.502)	(0.593)			
Post×Hyundai				1.964	0.890	0.337
				(1.401)	(0.566)	(0.413)
Post×Kia				1.902	0.945	0.380
				(1.347)	(0.585)	(0.457)
Post×Genesis				3.317**	3.291***	2.773**
				(1.333)	(0.573)	(0.387)
Control Variables						
Product Characteristics	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Brand Fixed Effects	✓	✓	✓	✓	✓	✓
Month Fixed Effects				✓	✓	
N	1,741,861	1,487,706	1,365,042	1,741,861	1,487,706	1,365,042
R-sq	0.788	0.829	0.825	0.788	0.828	0.824
adj. R-sq	0.788	0.829	0.825	0.788	0.828	0.824

Note: The unit of observations is at the VIN-month level and standard errors are clustered at the brand level. The dependent variable is the new price of a car i in month t. Asterisks represent significance level at $1\%^{(***)}$, $5\%^{(**)}$, and $10\%^{(*)}$.

market entry (April 2023 to September 2023) and six months post-entry (October 2023 to March 2024).

Columns (1) through (3) report the price change without brand-specific interactions, while Columns (4) through (6) include interaction terms between the post-entry period and specific Hyundai Group brands (Hyundai, Kia, and Genesis). The first three columns include different control groups: Column (1) uses all brands, including other domestic, German, and foreign brands; Column (2) restricts the control group to other domestic brands; and Column (3) does not include a control group, comparing Hyundai's new car prices before and after October 2023. The results from columns (1) to (3) indicate that the overall price change post-entry is statistically insignificant across all specifications. Specifically, the coefficient for the post-entry period is -2.669 in Column (1), 1.148 in Column (2), and 1.494 in Column (3), none of which are statistically significant. This suggests that, on average, Hyundai's entry into the secondary market did not lead to a significant change in new car prices when considering the entire set of brands or even when focusing on domestic brands alone.

However, a more granular analysis in Columns (4) through (6), which separates the impact by individual brands, reveals important differences. For Hyundai and Kia, the coefficients of their respective interaction terms with the post-entry period are positive but statistically insignificant, indicating that their new car prices remained stable and did not significantly change following the secondary market entry. This implies that Hyundai's overall strategy did not substantially alter the pricing of its more mainstream models. In contrast, the results for Genesis, Hyundai's luxury brand, tell a different story. Across all specifications, the coefficients for the interaction term between the post-entry period and Genesis are positive and statistically significant. Specifically, the coefficients range from \$3,325 in Column (4) to \$3,703 in Column (6), all significant at conventional levels. This indicates that new car prices for Genesis models increased notably following Hyundai's entry into the secondary market. The substantial price increase suggests a deliberate strategy by Hyundai to enhance the new car prices of Genesis by leveraging the secondary market. This aligns with the observed behavior in the secondary market where Hyundai offered the highest trade-in premiums for Genesis models, which depreciated more rapidly compared to other brands. By offering substantial premiums in the trade-in market, Hyundai likely aimed to increase the perceived value and resale appeal of Genesis models, translating into higher willingness to pay for new Genesis cars. These findings emphasize that Hyundai's market entry was not merely about participating in the used car market but was strategically aimed at influencing new car prices, particularly for its luxury segment. This nuanced impact highlights the complex interplay between secondary market dynamics and primary market pricing strategies employed by manufacturers.

Qualitative Evidence

The empirical evidence presented in the previous section demonstrates that Hyundai's entry into the secondary market was strategically targeted at enhancing the resale value and new car prices of Genesis models. To further substantiate these findings, I conducted interviews with key stakeholders in the industry, including an anonymous Hyundai employee and the CEO of a leading used car company in South Korea. Their insights provide qualitative support for the observed changes in Hyundai's market behavior.

> *"Hyundai's operating profit really outperformed in 2023. One reason for this [success] is [owing to] the success of Genesis. Typically, in the car manufacturing sector, the profit-cost margin isn't that high. Excluding some SUV models, Hyundai car's margin is about 2-5%. However, in the case of Genesis, the margin exceeds 20%."*
>
> — Anonymous Hyundai Employee (August 25, 2023)

This statement highlights that Hyundai's strategic focus on the Genesis brand has some merits, which aligns with the quantitative findings showing significant increases in new car prices for Genesis following Hyundai's engagement into the secondary market. The substantial profit margins mentioned suggest that Hyundai has an incentive to leverage the resale value of Genesis to justify higher primary market prices, reinforcing the notion of targeted interventions in the used car market to enhance brand positioning.

> *"One of the most important things for automobile companies is to justify the retail value [of their car]. That way, people who have already bought the car won't complain about their purchases. Hyundai's current main [sales] target is the retail value of Genesis. They're trying to elevate the Genesis brand image up to the level of foreign brands. The BMW 5 Series' prices range from \$60,000 to \$80,000, and Genesis has almost caught up to that range."*
> — Hyundo Shin, CEO of Youcar (January 12, 2023)

The CEO's perspective emphasizes Hyundai's strategic intent to elevate the Genesis brand to compete directly with luxury foreign brands, such as BMW. By maintaining a high resale value, Hyundai aims to protect the perceived worth of Genesis vehicles, thereby justifying premium new car prices and enhancing customer satisfaction. This aligns with the regression results showing that Hyundai's market interventions were most impactful for Genesis, where trade-in premiums were strategically used to bolster the luxury brand's appeal.

These qualitative insights from industry experts reinforce the empirical evidence that Hyundai's entry into the secondary market was a deliberate and strategic effort, specifically aimed at influencing new car prices for its luxury Genesis line rather than a general market strategy. The interviews shed light on Hyundai's motivations and strategic objectives, revealing the company's focus on elevating the Genesis brand to compete with foreign luxury brands and justifying its retail value. This aligns with the empirical results, which show that while Hyundai's overall market strategy had little impact on the prices of mainstream models of Hyundai and Kia, it significantly boosted new car prices for Genesis. This targeted approach reflects Hyundai's calculated effort to enhance the value proposition of Genesis, potentially driving profitability in both the primary and secondary markets.

6 Implications

The findings of this research offer implications for both business practitioners and government policymakers, highlighting how strategic engagement in the secondary market can influence broader market behavior and stakeholders both in secondary and primary markets.

First, from a managerial perspective, this study provides a critical lesson that the secondary market should not always be viewed as a threat to new product sales but could also be considered as an additional channel through which they can strengthen the overall performance of the primary market. By actively participating in the secondary market, manufacturers can strategically adjust the resale value of their products, which, as shown in this study, can directly boost the value perception and profitability of new goods. This approach challenges the conventional view that secondary markets primarily cannibalize new product sales, instead revealing that these markets can complement and enhance primary market outcomes when leveraged strategically.

In practice, several companies across industries are already engaging with the secondary market to reinforce their primary market strategies. Apple, for instance, collects used iPhones through its trade-in program but avoids flooding the market with secondhand Apple devices. While some iPhones are refurbished and resold, Apple strategically disassembles and recycles many of the traded-in devices (Apple, 2024). This approach helps limit the supply of used iPhones available for resale and thus, maintain strong resale values, ensuring that secondhand iPhones do not saturate the market and lower their worth. By controlling the supply in this way, Apple enhances the perceived value of new iPhones, allowing them to sustain a premium price point. This carefully managed strategy strengthens both Apple's brand and their pricing power in the primary market. BMW employs a unique strategy with its BMW Premium Selection program. The company leases new cars in Germany, and these leased vehicles, often with low mileage (less than 15,000 kilometers) and a young age (under two years), are then exported to emerging markets in Eastern Europe, such as Hungary. By sending these nearly new cars to markets where demand for new cars is lower, BMW avoids oversupply in Germany, which could depress prices for both new and used cars. This enables BMW to manage the balance of supply across regions, maintaining higher prices and protecting the brand's premium positioning in its primary market. Tesla takes a more direct approach by not allowing lease buyouts, giving the company full control over the number of Teslas driving in the road. By restricting consumers from buying out their leases and keeping more cars under its control, Tesla can manage the supply of used vehicles, protecting the brand's exclusivity and maintaining higher residual values. This strategy allows Tesla to avoid market saturation and retain a strong pricing position for both new and used vehicles. Lastly, in the sports and events market, SeatGeek has made it easy for consumers to resell unused tickets through their platform. By providing a user-friendly resale process, including price comparisons based on seat location, SeatGeek reduces the net cost of purchasing event tickets. This ease of resale lowers the perceived risk of buying tickets in the primary market, stimulating demand and making purchasing decisions less risky to consumers. While these strategies differ across industries, they all illustrate a common principle: engaging with the secondary market can be an effective way to enhance the value of primary market products. Whether through controlling supply, enhancing resale values, or facilitating consumer transactions, companies can strategically harness the secondary market to complement and strengthen their overall market position.

Second, this research provides important policy implications. The primary motivation behind allowing Hyundai's entry into the secondary market was to address quality concerns and fraud issues in the used car market in South Korea. Policymakers aimed to solve persistent lemon problems and enhance consumer trust by introducing a reputable player like Hyundai into the market. This intervention was expected to reduce the transaction costs associated with purchasing used vehicles by providing a more reliable alternative to traditional dealerships, thereby improving market efficiency and consumer welfare. Indeed, Hyundai's presence in the secondary market likely alleviates many of these consumer concerns, offering a more transparent and hassle-free experience for used car buyers who value the assurance of dealing with a trusted manufacturer.

However, while addressing these visible market failures, it is crucial to consider the less visible consequences of such policy interventions. This study reveals the complex interplay between the secondary and primary markets, demonstrating that changes in one can have significant implications for the other. Specifically, the entry of a major manufacturer like Hyundai into the secondary market can accompany an increase in new car prices, which might lead to increased exploitation of consumer surplus in the primary market. This dynamic is consistent with theoretical work on market segmentation and price discrimination, where firms leverage control over secondary markets to influence primary market outcomes (Anderson and Ginsburgh, 1994; Waldman, 1997). These findings suggest that while policies aimed at improving secondary market conditions can have immediate benefits, they may also introduce new forms of consumer exploitation that are less apparent. Therefore, policymakers need to be mindful of the broader external economic impact when designing policies that affect secondary markets. It is not enough to consider only the direct benefits within the secondary market, such as reduced fraud or lower transaction costs; the potential for unintended consequences in the primary market must also be taken into account. Policies that allow manufacturers to engage in secondary markets need to be crafted with a nuanced understanding of how these actions will influence both the resale values and the pricing strategies for new products. By considering these dual effects, regulators can better balance the benefits of increased market transparency and competition with the need to protect consumers from potential price exploitation.

7 Conclusion

This research examines the importance of understanding the interconnected nature of primary and secondary markets. The findings underscore that Hyundai's entry into the secondary market was not just a response to consumer demand for transparency and trust in used car transactions but also a deliberate strategy to influence new car pricing, particularly for its luxury Genesis brand. By offering substantial trade-in premiums, Hyundai was able to enhance the perceived value of its vehicles, translating into higher prices in the primary market. This strategic approach provides a compelling example of how manufacturers can leverage secondary markets to optimize their broader market positioning and profitability. The implications of this research are twofold: For manufacturers, it demonstrates the potential to use secondary markets strategically to boost primary market sales, turning what is often viewed as a competitive threat into a powerful tool for market differentiation and value creation. For policymakers, it emphasizes the need for a comprehensive approach to market regulation that carefully weighs both the benefits and potential downsides of allowing manufacturers greater control over secondary markets. This dual perspective is essential for making informed decisions that promote fair and efficient market outcomes.

This study is not without limitations. The analysis primarily relies on a single case study of Hyundai in the South Korean automobile market, which may limit the generalizability of the findings to other contexts or industries. The unique market conditions, regulatory environment, and brand dynamics in South Korea may differ significantly from those in other regions, suggesting that similar outcomes may not necessarily occur elsewhere. Future research should consider examining similar interventions in different markets or industries to validate the broader applicability of these findings. Comparative studies across various countries or sectors could provide deeper insights into how different market structures and regulatory frameworks influence the interplay between primary and secondary markets. Moreover, future research could also explore the long-term effects of manufacturer participation in secondary markets on consumer welfare, brand loyalty, and market competition. Experimental or structural approaches could offer more robust evidence on the impact of secondary market engagement on primary market outcomes, further enriching the understanding of this complex relationship.

To sum up, this research opens new avenues for both academic inquiry and practical application, emphasizing the need for continued exploration of the strategic and regulatory implications of secondary market engagement by manufacturers. By expanding the scope of investigation to include diverse contexts and employing innovative research methodologies, future studies can build on these findings to offer a more comprehensive understanding of the evolving role of secondary markets in modern economic landscapes.

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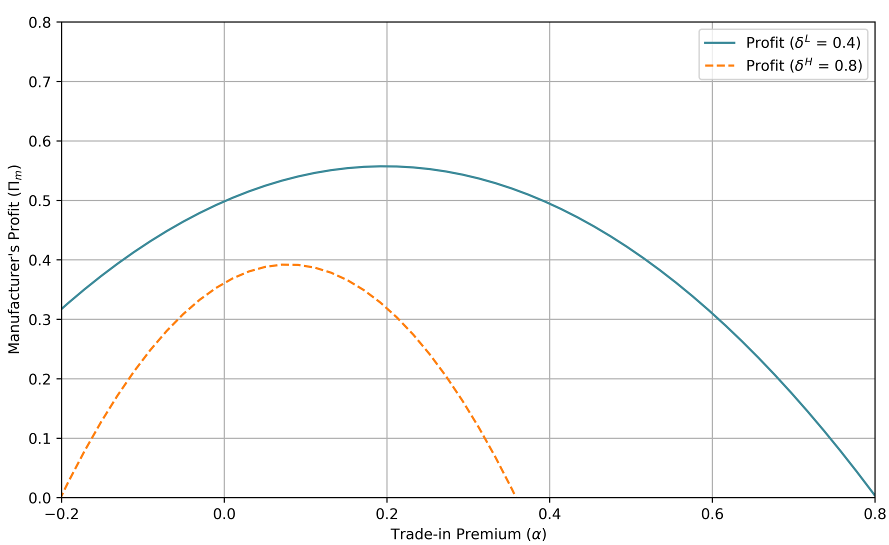
Appendix

A Consumer Responsiveness to $\delta^L = 0.4$ and $\delta^H = 0.8$ when $\lambda = 1$

In the context of a manufacturer controlling the entire secondary market (i.e., when $\lambda = 1$), the dynamics of trade-in premiums take on a more pronounced role. This scenario, as shown in Figure A1, highlights every additional dollar spent by the manufacturer to increase α has an immediate and direct effect on the q_{nn} segment (new-new car buyers). Because the manufacturer controls the secondary market, changes in α dramatically alter the utility consumers derive from trading in their old cars, leading to sharp shifts in the costs the manufacturer incurs than Figure A1. As a result, even small increases in α can cause swift and significant changes in profit, with both high-durability (δ^H) and low-durability (δ^L) products experiencing steeper declines in profitability. This is due to the rapid increase in costs as the trade-in premium incentivizes consumers to transition between car segments. Consequently, the profit function steepens, reflecting diminishing returns from further increases in α and the manufacturer reaches its profit-maximizing trade-in premium more quickly when they control the secondary market.

Figure A1. Manufacturer Profit and Trade-in Premium ($\lambda = 1$)



Note: The parameters are set to $\delta^L = 0.4, \delta_r^L = 0.42, \delta^H = 0.8, \delta_r^H = 0.82, c = 0.3, c_r = 0.0005, w = 0.24, \lambda = 1$

B Identifying Private Information from Publicly Available Data

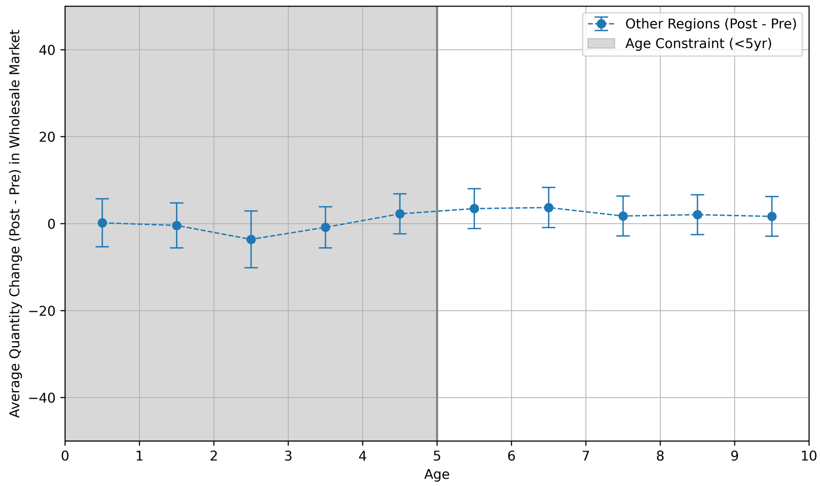
To identify Hyundai's trade-in cars from publicly available data, a Difference-in-Difference (DiD) model is estimated to analyze the changes in wholesale quantities of vehicles purchased at Hyundai's headquarter before and after October 2023, specifically focusing on vehicles registered in Seocho as their home address. This approach helps to verify whether the vehicles with Seocho registration as home address are indeed the cars purchased by Hyundai as part of their trade-in program. The model is specified as follows:

$$q_{Art} = \sum_{A=1}^{10} 1(A) \cdot (\beta_{1A} + \beta_{2A} Seocho_r + \beta_{3A} Post_t + \beta_{4A} Seocho_r \times Post_t) \\ + \gamma_r + \tau_t + \varepsilon_{Art}$$

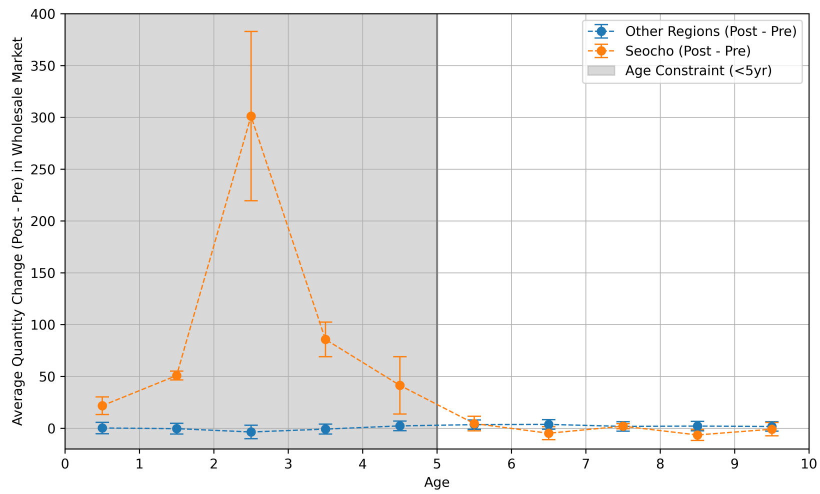
where q_{Art} represents the wholesale quantity of used cars of age A purchased in region r during period t. The variable $Seocho_r$ is an indicator that equals 1 if the region r is Seocho, while $Post_t$ equals 1 if the time period t is after October 2023, inclusive. The model includes region and time fixed effects, γ_r and τ_t, respectively, to control for unobserved heterogeneity across regions and over time. The coefficients of interest are β_{3A}, capturing the average change in wholesale quantities post-entry among all regions except Seocho, and β_{4B}, measuring the average change in wholesale quantities post-entry in Seocho. The aim is to interpret β_3 and β_4 to verify whether vehicles registered as Seocho are linked to Hyundai's trade-in activities.

Figure A2 provides a comparative analysis of the change in the quantity of vehicles purchased in the wholesale market before and after Hyundai's trade-in program entry, focusing on vehicles registered in Seocho versus other regions. The first subfigure (i) shows data from regions other than Seocho, while subfigure (ii) shows data from Seocho. The shaded area represents vehicles aged five years or less, which Hyundai is mandated to purchase under government regulations. The results indicate no statistically significant increase in vehicle quantities post-entry across ages 1 to 10 in regions other than Seocho. Figure A2 (i) suggests that outside the Seocho region, Hyundai's entry does not affect the quantity purchased in the secondary market. In contrast, the second subfigure (ii) focuses on Seocho and presents a different pattern, showing a significant increase in the quantity of vehicles purchased, particularly those aged between two and three years. This spike indicates a dramatic

Figure A2. **Average Quantity Change in Wholesale Market Post-Entry across Age**



(a) Other Regions (Post - Pre)



(b) Seocho (Post - Pre)

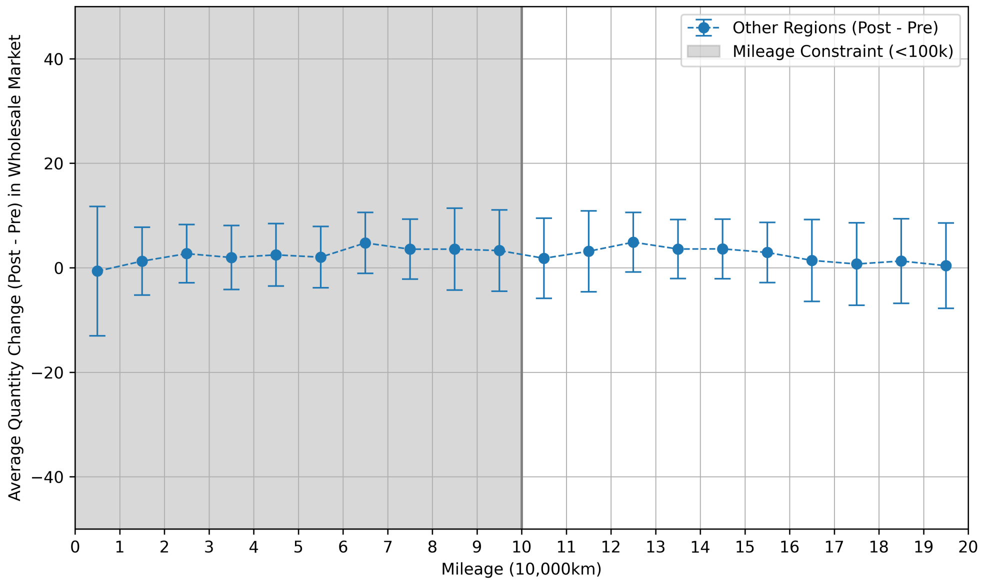
increase in wholesale cars purchased tied to Hyundai's activities, supporting the hypothesis that these vehicles, registered as Seocho, are potentially Hyundai's trade-in cars. The targeted increase in quantities across ages less than five suggests a consistent intervention promised by Hyundai, further enhancing the hypothesis that Hyundai purchased their cars to headquarter address. This evidence supports the identification of Seocho-registered vehicles as linked to Hyundai's program, as these observed changes align with Hyundai's headquarter address.

Building upon the age-based analysis, Figure A3 extends the examination by considering vehicle *mileage* to further assess the potential identification of Hyundai's trade-in cars. The first subfigure (i) illustrates the changes in vehicle quantities across regions other than Seocho, highlighting that there is no statistically significant variation in quantities across different mileage bands after Hyundai's trade-in activities began. This lack of noticeable changes indicates that Hyundai's impact on the market is not detectable in these areas, suggesting a lack of influence in wholesale used car market outside Seocho. The second subfigure (ii) focuses on Seocho and highlights a distinct pattern: there is a significant increase in the quantity of vehicles with lower mileages, particularly those in the 20,000 to 40,000 km range. As the mileage approaches 100,000 km, the quantity of vehicles decreases sharply and nearly vanishes once the mileage surpasses 100,000 km. This pattern aligns with the understanding that Hyundai's targeted efforts are specifically aimed at acquiring vehicles not just by age but also within particular mileage ranges. The significant concentration of lower-mileage vehicles reinforces the identification of Seocho-registered vehicles as likely trade-ins by Hyundai, supporting the hypothesis that these observed trends are directly linked to Hyundai's strategic activities.

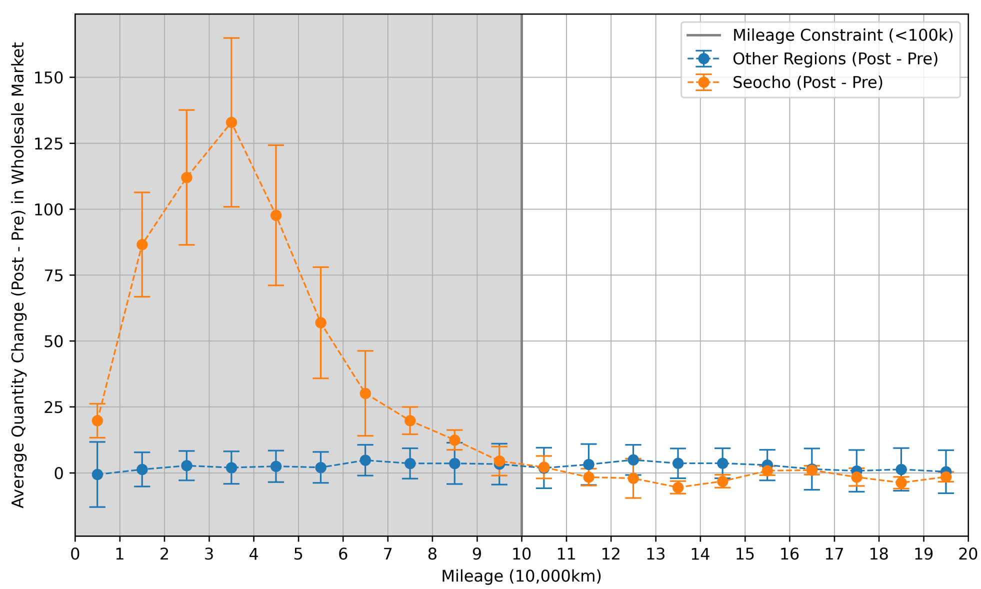
Figure A4 conducts a falsification test using *freight* cars, a vehicle category not involved in Hyundai's trade-in activities, to validate the identification of trade-in cars. This figure serves as a control, showing that there should be no significant changes in the quantities of freight vehicles purchased, either by age or mileage, to reinforce that the observed effects in Seocho are specifically tied to passenger vehicles likely associated with Hyundai's trade-in program. The flat trends across these categories confirm that the Seocho-specific patterns are not due to broader market changes or unrelated factors, but rather are directly connected to Hyundai's entry into the secondary market selling passenger cars. This lack of significant changes in freight vehicles strengthens the argument that Seocho-registered vehicles showing significant increases in quantity are indeed tied to Hyundai's trade-in efforts. The falsification test confirms the distinct nature of Hyundai's influence, which does not extend to vehicle types not involved in their CPO program, further validating the valid use of my publicly available data to identify Hyundai's trade-in cars.

Figure A5 extends the falsification analysis by examining vehicles from other manufacturers, including other domestic brands, three major German automakers, and other foreign manufacturers, which are not involved in Hyundai's trade-in activities. This analysis aims to validate that the patterns observed in Figure A2 and Figure A3 are not driven by broader market trends that could impact

Figure A3. **Average Quantity Change in Wholesale Market by Mileage Post-Entry across Mileage**



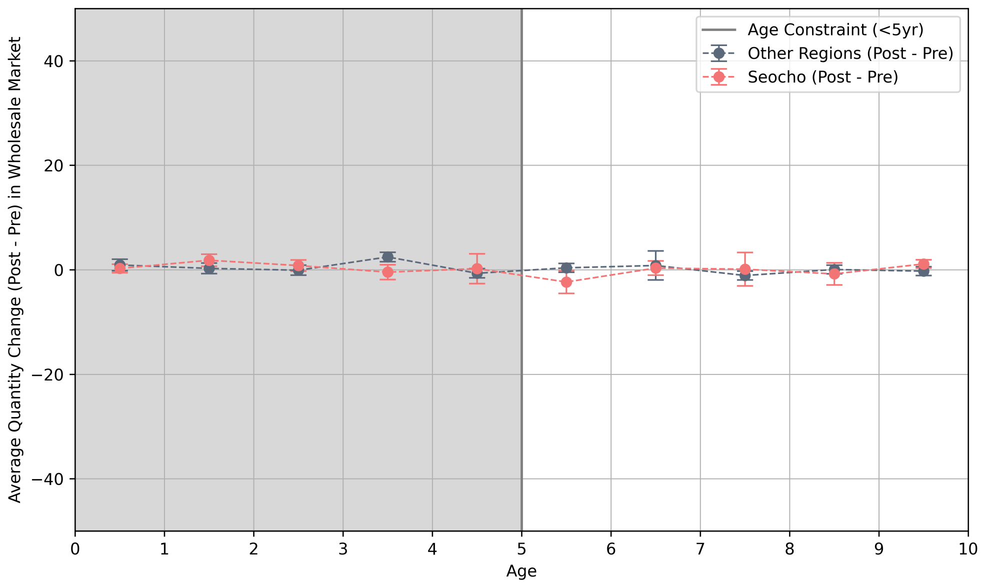
(a) Other Regions (Post - Pre)



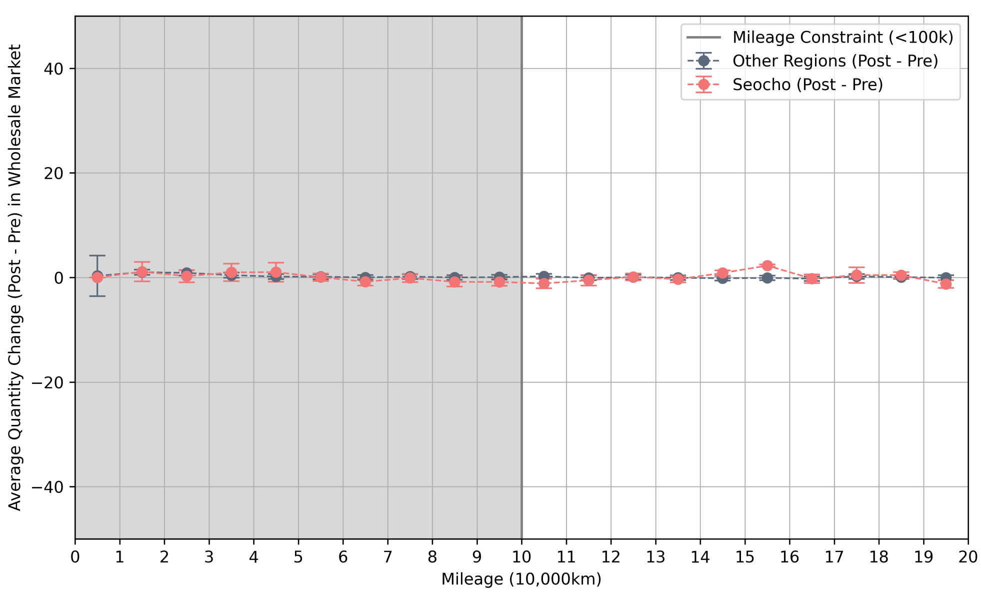
(b) Seocho (Post - Pre)

all automakers, but are specifically associated with Hyundai's trade-in program. Although there is some variability and larger standard errors, the data for these other brands show no statistically sig-

Figure A4. Falsification Test using Freight Cars



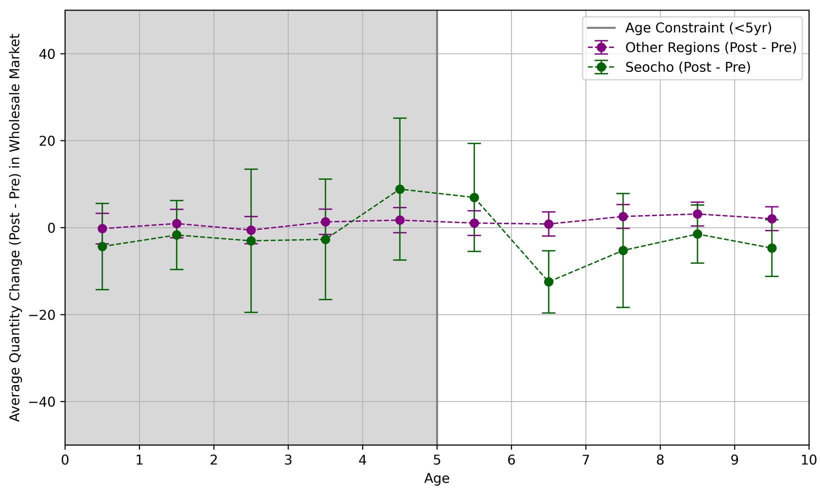
(a) Age - Other Regions vs. Seocho (Post - Pre)



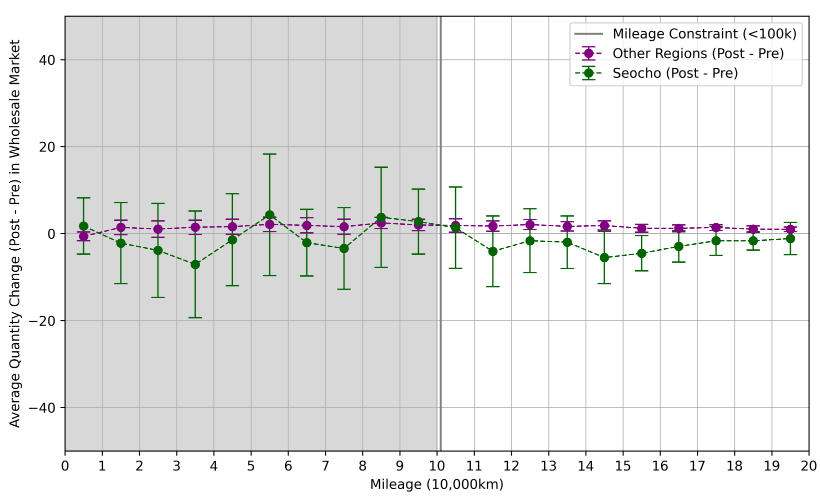
(b) Mileage - Other Regions vs. Seocho (Post - Pre)

nificant shifts in the quantities purchased in either Seocho or other regions post-entry. This reinforces the hypothesis that the changes observed in Seocho are unique to Hyundai's trade-in efforts, as the absence of significant deviations in other brands confirms that the observed patterns are not due to external factors but are directly tied to Hyundai's strategic actions in the trade-in market. This finding further supports the identification of Seocho-registered vehicles as being likely associated with Hyundai's trade-in activities, highlighting the distinct nature of Hyundai's impact compared to other automakers.

Figure A5. Falsification Test using Other Vehicle Manufacturers



(a) Age - Other Regions vs. Seocho (Post - Pre)



(b) Mileage - Other Regions vs. Seocho (Post - Pre)

C Selection Bias via Information Advantage of Hyundai

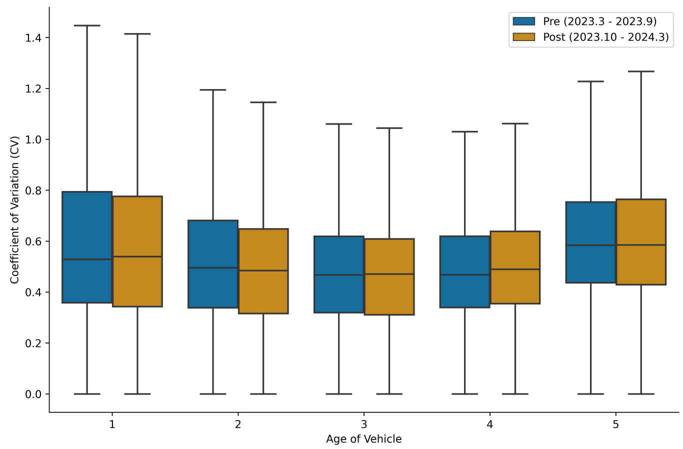
This section explores alternative mechanisms that could explain the observed trade-in premiums discussed in the section 5, specifically focusing on the role of information asymmetry. Since Hyundai manufactured all Hyundai-branded vehicles sold in the secondary market, the company may possess proprietary information about the unobservable characteristics of these cars, creating an informational advantage over independent dealers. This informational asymmetry could drive Hyundai's trade-in premiums and affect dispersed price in the secondary market. To illustrate the potential impact of information asymmetry, consider the following scenario:

Table 13. Illustrative Scenarios of Information Asymmetry in Trade-In Offers

		Observables	Unobservables	Dealer Offer	Hyundai Offer
Pre	$\mathbb{A}$	15,000 km / 2 years	Smoker / 3 dogs / no oil change	\$10,000	-
	$\mathbb{B}$	15,000 km / 2 years	Non-smoker / no dogs / frequent oil change	\$10,000	-
Post	$\mathbb{A}$	15,000 km / 2 years	Smoker / 3 dogs / no oil change	\$10,000	\$9,000
(S1)	$\mathbb{B}$	15,000 km / 2 years	Non-smoker / no dogs / frequent oil change	\$10,000	\$11,000
Post	$\mathbb{A}$	15,000 km / 2 years	Smoker / 3 dogs / no oil change	\$10,000	\$11,000
(S2)	$\mathbb{B}$	15,000 km / 2 years	Non-smoker / no dogs / frequent oil change	\$10,000	\$11,000

The table presents some scenarios to illustrate the potential effects of Hyundai's informational advantage on trade-in pricing. In the Pre period, both individuals $\mathbb{A}$ and $\mathbb{B}$ own cars with identical observable characteristics: 15,000 km and 2 years old. However, there are critical unobservable factors that differentiate them—$\mathbb{A}$ is a smoker with pets and lacks regular maintenance, while $\mathbb{B}$ is a non-smoker with meticulous maintenance habits. Dealers, lacking access to these unobservable characteristics, offer the same price of \$10,000 to both. In the post period, two scenarios illustrate how Hyundai's informational advantage might manifest. Scenario 1 (Post S1) assumes Hyundai can access the unobservable details due to their role as the original manufacturer. As a result, Hyundai offers \$11,000 to $\mathbb{B}$, recognizing the car's better condition, and only \$9,000 to $\mathbb{A}$, reflecting the poorer unobservable conditions. Dealers continue to offer \$10,000 to both, leading to $\mathbb{A}$ accepting the dealer's offer and $\mathbb{B}$ accepting Hyundai's. This outcome introduces greater price dispersion due to Hyundai's selective pricing based on hidden information. Scenario 2 (Post S2) reflects the mechanism posited in my theory, where Hyundai aims to uniformly enhance the resale value, regardless of the unobservables. Here, Hyundai offers an equal premium of \$1,000 above the dealer's offer to both individuals, maintaining a consistent pricing strategy and thus keeping price dispersion unchanged.

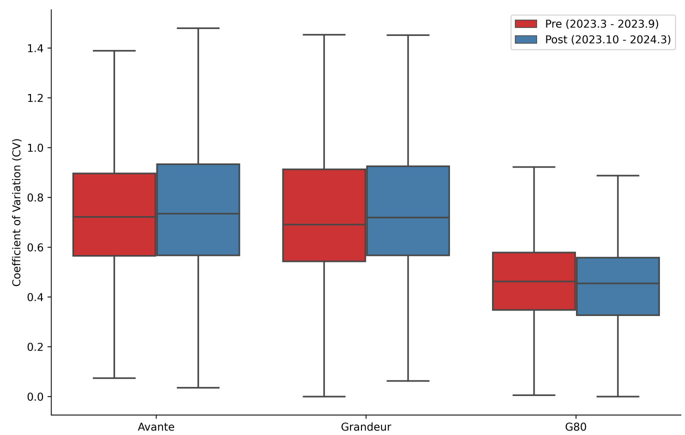
Figure A6. Distribution of Coefficient of Variation (CV) across Vehicle Age



To empirically test whether Hyundai's pricing strategy introduces selection bias due to information asymmetry or aligns with a broader resale value enhancement goal, I employ a cell-based approach to evaluate price dispersion. Specifically, each cell is defined by combining variables such as odometer readings, vehicle age, fuel type, and model. I discretized odometer readings into 5,000 km intervals, ranging from 0 to 400,000 km, creating 80 mileage groups. The vehicle age variable is groupted into 24 groups corresponding to each year of a car's age, from 1 to 24 years. Fuel types are categorized into four groups: Diesel, Gasoline, Electric, and Hybrid. Finally, I identify 750 distinct vehicle models within the dataset. Each cell is thus a unique combination of these factors, amounting to a comprehensive grouping based on observable vehicle characteristics. For example, a specific cell consist of vehicles with mileage between 1 and 5,000 km, aged 1 year, fueled by gasoline, and of the Grandeur model. Within each cell, I calculate the coefficient of variation (CV), defined as the ratio of the standard deviation (σ) to the mean price (μ) within each cell and compare $CV (= \sigma/\mu)$ before and after six months of Hyundai's entry using Hyudai Motor Group's cars. Thus, a higher CV would indicate increased price dispersion, potentially pointing to Hyundai's informational advantage influencing their pricing strategy. Conversely, a lower or insignificant CV change would reject the null saying there exists selection bias due to Hyundai's entry.

Figure A6 shows the distribution of the coefficient of variation (CV) for different vehicle age groups, comparing six months of data before (April 2023 to September 2023) and after (October 2023 to March 2024) Hyundai's secondary market entry. The x-axis represents the vehicle age, ranging from 1 to 5 years, while the y-axis shows the CV values. Each age group contains two box plots: one for the pre-entry period and another for the post-entry period.

Figure A7. Distribution of Coefficient of Variation (CV) across Model (All Ages)

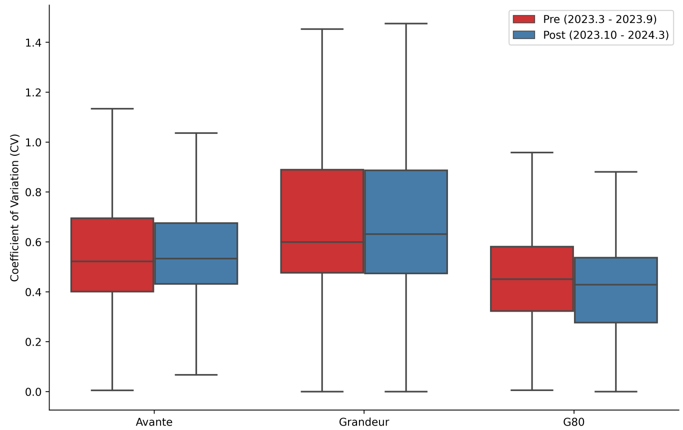


The distribution of CV shows a decreasing trend as the vehicle age increases from 1 to 4 years, which indicates that price dispersion tends to be higher for younger vehicles, particularly those within the first 12 months. This higher CV in age 1 can be attributed to several factors, such as varying reasons for early resale (e.g., financial distress, dissatisfaction with the vehicle, or rapid changes in market conditions). As vehicles age until 4, the factors influencing price dispersion become more consistent, likely due to more uniform wear and tear, leading to a decrease in CV. Interestingly, the CV rises again at age 5, suggesting that as vehicles become older, the quality and maintenance history begin to diverge, contributing to increased price dispersion. This variation is driven more by the aging process and less by factors relevant to very new cars.

Regarding the distribution of box plots, there is minimal change in CV between the pre- and post-entry periods across all age groups, suggesting that Hyundai's market entry did not significantly impact the overall price dispersion within these categories. Although a slight increase in CV is observed for the age 1 group in the post period, this is counterbalanced by a decrease in CV for vehicles aged 2 and 3. This pattern does not support the argument that Hyundai's informational advantage led to increased price dispersion post-entry. Instead, it suggests that Hyundai's participation in the secondary market did not alter price variations in a manner consistent with exploiting private information.

Figure A7 presents the distribution of CV for three flagship models of Hyundai Motor Group: Avante (compact car), Grandeur (mid-sized sedan), and G80 (large-sized luxury sedan). The x-axis represents the model types, and the y-axis shows the CV values, with two box plots for each model depicting pre-entry (April 2023 to September 2023) and post-entry (October 2023 to March 2024) pe-

Figure A8. Distribution of Coefficient of Variation (CV) across Model (Age $\leqq$ 5)



riods. The results indicate that there is minimal to no significant change in price dispersion across the models following Hyundai's market entry. For the Avante, the upper quartiles show a slight increase in the post-entry period, although the median remains stable, indicating that most of the price dispersion changes occur in the higher price ranges. For the G80, there is a slight decrease in both the upper and lower quartiles, suggesting a narrowing of price dispersion, possibly due to Hyundai's trade-in premiums targeting luxury models to stabilize resale values. Grandeur, representing mid-sized sedans, exhibits little to no change in its CV values, reinforcing that Hyundai's entry did not notably affect price variations in this category.

Figure A8 refines the analysis by focusing on vehicles aged 5 years or younger, again examining the Avante, Grandeur, and G80 models. The x-axis remains the same, listing the three models, and the y-axis displays the CV values for both pre- and post-entry periods. The findings are consistent with those from Figure A7, showing that there is little evidence of increased price dispersion due to informational advantage after Hyundai's market entry. Overall, both graphs counter the argument of increased price dispersion due to informational asymmetry, especially given that the changes observed are minimal and not consistently upward across different models and age groups. Instead, these results suggest that Hyundai's strategy did not result in exploiting informational advantages to a degree that would significantly alter price variations within the secondary market.