Sunk Cost Fallacy in Driving the World's Costliest Cars

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Abstract

Does the sunk cost fallacy affect decision-makers in repeated situations? We develop a behavioral model of usage of a durable good with mental accounting for sunk costs over some time horizon. The model predicts higher-than-rational usage that attenuates over time, where the rate of attenuation is faster with higher sunk costs. It nests rational behavior as a special case. We take the model to data on 8,264 cars purchased in Singapore between 2000-2013, when continuing government policy caused the sunk cost associated with buying a new car to vary substantially. Based on structural estimation, we find robust evidence that sunk costs did affect behavior. The elasticity of driving with respect to the sunk cost is 0.050 (s.e. 0.016). An increase in the sunk cost by S$13,038 (the outcome of government policy between January 2009 and June 2013) would be associated with an increase in monthly driving by 90 kilometers or 5.8% in the first four years of ownership. Our results are robust to various checks including alternative explanations in terms of selection, the specification of sunk costs, and salience of sunk costs. Similarly, in a dataset of Hong Kong car buyers, we find that driving was influenced by sunk costs.

Keywords: sunk costs, mental accounting, behavioral economics, durable goods

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1 Introduction

> *"Customers who had initially paid more for a season subscription to a theater series attended more plays during the next 6 months, presumably because of their higher sunk cost in the season tickets" (Arkes and Blumer 1985: 124).*

Economists and psychologists have long been interested in the effect of sunk costs on consumer choice and organizational behavior (Thaler 1980 and 1990). Sunk costs cannot be avoided regardless of future actions. Being irreversible, they should not play any role in rational decision making. Yet, sunk costs have been implicated in apparently irrational decisions across multiple contexts.

In what Eyster (2002) described as the "most convincing single experiment", Arkes and Blumer (1985) gave unannounced price discounts at random to people buying season tickets at a university theater. Over the first half of the season, individuals who paid full price attended more shows than those who received discounts (4.1 vis-a-vis 3.3 out of 5 shows). In the second half of the season, however, the two groups did not behave differently. Gourville and Soman (1998) observed "payment depreciation" among members of an athletic club: monthly attendance peaked when the members paid their half-yearly installment, and then declined with time. In a field experiment at an all-you-can-eat-pizza restaurant, people who received a discount ate less (Just and Wansink 2011). The three studies suggest that higher sunk costs induce more consumption. The first two studies also indicate that the effect of sunk costs declines over time.

However, in other field experiments, consumers given random unannounced discounts did not evince the sunk cost fallacy. Differences in the amounts that Zambian consumers paid for Clorin, a chemical to treat drinking water, did not affect their use of the chemical to treat water (Ashraf et al. 2010). In Kenya, there was no clear relation between the net price that consumers paid for insecticide-treated bed nets and their use of the nets (Cohen and Dupas 2010).[2]

How do sunk costs affect the use of a durable good over time? The effect of sunk costs on decision-making in repeated situations such as durable good usage has important implications

[2] In laboratory experiments, Phillips et al. (1991) and Friedman et al. (2007) also did not find evidence of the sunk cost fallacy.

for management of businesses and public administration as well as consumer behavior.[3]

A priori, sunk costs might affect the use of a durable good to a lesser or greater extent as compared with once-only consumption. Since the cost of (repeated) mistakes is larger, consumers might invest more effort to correct irrational biases in decision-making. On the other hand, consumers might pay more attention to the sunk cost, resulting in an even larger influence on behavior.

The effect of sunk costs on durable good usage remains an open question. Although Cohen and Dupas (2010) studied the use of bed nets, which are durable, they recorded usage just once. The Arkes and Blumer (1985) experiment and Gourville and Soman (1998) study pertain to usage of a facility, which differs from a durable good in that increased consumption does not affect the subsequent availability or quality of the good. Buyers of season tickets and members of the athletic club would not attend less to stretch out use of the facility.

Here, we investigate whether sunk costs influence use of a durable good in the context of the Singapore market for cars. Car usage is an attractive setting for investigation of the relation between sunk costs and durable good usage. People have many years of experience with cars, and usage is sustained over long periods of time. For instance, in U.S. metropolitan areas, Hastings and Shapiro (2013) find that households engaged in mental accounting for expenditure on gasoline. The Singapore context is particularly attractive for several reasons. By design, government policies to restrict car ownership require buyers of new cars to make payments that are only partially refundable, and so, impose explicit sunk costs. Over time, these policies have generated substantial variation in the sunk costs incurred in new car purchases (and incidentally, caused Singapore cars to be the world's most expensive). The government policies are long-standing and are repeatedly publicized, and so, the sunk costs are certainly salient to people in Singapore.

[3]In organizational contexts, managers have been observed to increase investment in the face of deteriorating conditions. Such "escalation of commitment" has been interpreted as being made to rationalize the decision-maker's earlier choice (Staw 1976; Staw and Hoang 1995; Staw et al. 1997). However, the same increase in investment could also be interpreted as the rational outcome of the decision maker's moral hazard, building of reputation (Kanodia et al. 1989; Camerer and Weber 1999), investment in a real option (Friedman et al. 2007; McAfee et al. 2010) or a memory short-cut (Baliga and Ely 2011). For instance, Camerer and Weber (1999) re-analyzed the Staw and Hoang (1995) data on escalation of commitment in the deployment of NBA basketball players. After accounting for the team managers' incentives through two-stage estimation, the effect of escalation of commitment was much reduced.

To investigate the effect of sunk costs, we first develop a behavioral model of mental accounting to understand how sunk costs might influence usage of a durable good over time. The model stipulates that buyers mentally account for the sunk cost over some time horizon (Gourville and Soman 1998; Thaler 1999). The mental transaction cost is a function of both the sunk cost and cumulative usage. The model implies that car usage increases with the sunk cost and attenuates over time, and, importantly, that the rate of attenuation over time increases with the sunk cost. The behavioral model of mental accounting nests rational behavior, where sunk costs do not affect decision making, as a special case.

Second, we take the model to structural estimation on a large-scale observational dataset comprising an unbalanced panel of 8,264 cars belonging to a single brand that were sold in Singapore between 2000-2013. For each car, we have the accumulated driving (in kilometers) at each service with the car dealer. During the period of study, the application of continuing government policies caused substantial downward and then upward variation in the sunk costs associated with buying a new car. We exploit this variation in structural estimation of the behavioral model.

Figure 1 depicts average monthly lifetime usage by vintage of car (year of purchase) for the most popular model in our sample, and the corresponding average retail price and the sunk portion of policy-related charges (Section 2 below explains the structure of the policy-related charges and sunk costs). The retail price of cars and policy-related sunk cost fell from 2000 to a low in 2009 and then rose sharply to 2013. As Figure 1 shows, average monthly lifetime usage is correlated with the retail price and policy-related sunk cost.

– Figure 1 here –

However, the correlation in Figure 1 between car usage and policy-related sunk cost can also be explained by selection, in particular, that when the prices of car are high, the people who buy cars are those who want to drive more. As a result, higher policy-related charges that cause higher car prices are associated with more driving. To distinguish selection from mental accounting for sunk costs, we draw a key implication from the behavioral model – that the rate at which usage attenuates with age of the car increases with the sunk cost. By contrast, selection need not imply any relation between car prices and the rate of attenuation or growth.

Figure 2 depicts monthly usage with age of the car for four vintages (2003, 2004, 2008 and

2009) of the most popular model in our sample over the first 48 months.[4] The retail price and policy-related sunk costs fell steadily from 2003 until 2009. Evidently, by Figure 2, the lower were the policy-related sunk costs, the lower the monthly usage tended to be, for all vintages of the car. More importantly, consistent with the behavioral model, the lower was the policy-related sunk cost, the slower was the rate at which usage attenuated with age of the car. Comparing the slopes of the four curves, the 2003 vintage is the steepest, and the 2009 vintage is the most gentle.

– Figure 2 here –

Our structural estimates suggest that the elasticity of usage with respect to the sunk cost of a car is 0.050 (s.e. 0.016). An increase in the sunk cost by S$13,038 (the outcome of continuing government policy between January 2009 and June 2013) would have been associated with an increase in monthly usage by 90 kilometers or 5.8% in the first four years of ownership. Our findings are robust to various checks including alternative explanations in terms of selection, the specification of sunk costs, and salience of sunk costs. We also estimated the behavioral model on a dataset of the same brand of cars in Hong Kong and found qualitatively similar results.

We interpret the relation between the attenuation of usage and the sunk cost as due to mental accounting for sunk cost. An obvious challenge to our interpretation is some form of selection. We address the challenge primarily by estimating the structural model in terms of first differences, rather than the levels of usage. Differencing abstracts from any heterogeneity among car buyers that does not vary with usage and car age, in particular, the direct effect of the retail price. In addition, we explicitly test two alternative explanations based on selection – demand shocks leading people to buy cars at high prices followed by reversion to the mean driving intensity, and high initial driving leading to more frequent breakdowns and attenuation of driving.

[4]Figure 2 presents usage between months 6 and 48. Our data is based on service visits. For the brand of cars in our sample, the first scheduled service is at cumulative usage of 12,000 kilometers. So, with average usage of 1,550 kilometers a month, the first service of the car would be in the eighth month. We observe that 186 cars (or about 2%) had their first service before the sixth month. According to the service schedule, these cars should have had much higher than average mileage. On the contrary, many of these cars had lower than average mileage. We infer that these cars were sent for service because of defects. Accordingly, to avoid confounds due to defects, we focus on usage after the sixth month of ownership.

Overall, our empirical analysis suggests that Singapore car buyers exhibited a sunk cost fallacy and did not self-correct (or did not fully self-correct) this decision bias over a period of 4 years. In the remainder of this paper, Section 2 describes Singapore government policies on car ownership and usage. Section 3 presents a model of mental accounting for sunk costs, Section 4 presents the empirical strategy, and Section 5 introduces the data. Section 6 reports structural estimates of the behavioral model and tests of alternative selection-based explanations, and Section 7 provides a comparative analysis using Hong Kong data. Section 8 discusses implications of our findings for policy and management, while Section 9 concludes.

2 Singapore Car Policies

Singapore is a small densely-populated city-state, which, like many other cities, faces the challenge of managing traffic congestion. Since 1975, the Singapore government has tackled traffic congestion in two ways – pricing road usage and limiting the vehicle population. While the government's policies to manage traffic congestion targets all vehicles, we focus on cars in the discussion below.

Initially, the government sought to limit the car population through a hefty tax, the "Additional Registration Fee" (ARF), on new car registrations. The ARF is based on the wholesale cost or import price of the car, which is officially called the "open market value" (OMV). At the time of writing, the ARF was set at 100% of OMV. (No cars are manufactured in Singapore. Since all are imported, the import price equals the wholesale cost.)

From 1990, the Singapore government explicitly limited the number of new car registrations by imposing a monthly quota for a "certificate of entitlement" (COE). A new car may be registered only with a COE, which is valid for ten years. The monthly quota is fixed by a formula in terms of a specified growth rate of the overall car population and the number of cars that were de-registered in the preceding time period. Twice a month, the government holds an auction for sale of the COEs. The official name for the price of the COE is the "quota premium", so-called because it arises only if the number of bids for COEs exceeds the quota. There has always been excess demand for the quota, giving rise to a non-negative

COE premium. Accordingly, in Singapore, the buyer of a new car pays:

$$\text{Retail price} = [1 + \pi_{ARF} + \pi_{tax}] \cdot \text{OMV} + \text{COE premium} + \text{Retail mark-up}, \tag{1}$$

where π_{ARF} and π_{tax} represent the rates of ARF and other taxes respectively.

One result of the Singapore's government policy to limit car ownership is that retail prices of cars are the world's highest. The average price of cars in our sample (what in Europe and the United States would be considered a typically middle class brand) is S$176,625 (US$114,692).

Buyers of new cars incur substantial policy-related sunk costs due to the rebate structures of the ARF and COE. Each COE is valid for ten years. Once a COE is used to register a new car, it cannot be detached and used for another car. The owner can only de-register the car (and sell it to a scrap dealer or ship it out of Singapore) and then apply to the government for a rebate on the COE. Within our period of study, the COE policy provided a rebate for de-registration of a car on the following terms. In the first two years of ownership, the rebate is capped at 80% of the COE premium, and so, 20% of the COE premium is sunk upon purchase of the car. Thereafter, the rebate is pro-rated by the days remaining until the car reaches 10 years of age. The COE expires after 10 years, after which the owner must either renew the COE or de-register the car.

Within our period of study, the ARF policy provided a rebate for de-registration of a car on the following terms. In the first five years of ownership, the rebate is capped at 75% of the ARF, and so, 25% of the ARF is sunk upon purchase of the car. Thereafter, the rebate is pro-rated, 5% step-wise, by the number of years remaining until the car reaches 10 years of age.[5] Figure 3 depicts the structure of the COE and ARF rebates and the corresponding sunk costs.

– Figure 3 here –

Consequently, in Singapore, the purchase of a new car involves two policy-related sunk costs:[6]

[5]At the end of the 10th year, the owner can get a rebate of 50% of the ARF by de-registering the car. Owners who renew the COE must forfeit the 50% ARF rebate.

[6]In the behavioral model, we also allow for part of the retail price, unrelated to government policy, to be sunk.

- Immediately after purchase, 20% of the COE premium is sunk. This cost does not vary with usage or age. From the day after the first 24 months, the car owner foregoes the pro-rated part of the COE premium each day, a cost that varies with age but not usage.

- Immediately after purchase, 25% of ARF is sunk. This cost does not vary with usage or age. From the day after the first 60 months, the car owner foregoes 5% of the ARF each year, a cost that varies with the year but not within the year and not with usage.

These sunk costs vary exogenously over time. Each month, the COE premium equilibrates the demand for new cars with the quota for new car registrations. Recall that the monthly quota is fixed according to a specific formula. With changes in demand and the quota, the COE premium varies, and so, the COE-related sunk cost of a new car purchase would vary.

The ARF and ARF-related sunk costs also fluctuate over time. Since the ARF is specified as a percentage of the OMV, any change in OMV due to changes in exchange rates or the manufacturer's wholesale pricing would affect the ARF, and therefore the ARF-related sunk cost. Moreover, within a single brand, the ARF on the various models differ according to the differences in their respective OMVs.

Figure 4 depicts the evolution of the retail price, ARF, COE premium, and policy-related sunk costs (related to ARF and COE premium) for the most popular model of car in our sample from 2000 to 2013. Evidently, the retail price, ARF, COE premium, and policy-related sunk costs varied considerably over time. The standard deviation of the policy-related sunk costs was S$3,993, compared with the mean sunk costs of S$17,155. We exploit this variation to identify the effect of sunk costs on car usage.

– Figure 4 here –

To better understand the policy background, Table 1, column (a), reports a regression of the COE premium on the COE quota, measures of driving costs, and macroeconomic factors. The statistically significant variables are the COE quota and macroeconomic factors (quarter and year fixed effects, not reported for brevity). The coefficient of congestion, as measured by the number of cars per kilometer of road, is negative but not precisely estimated. As an additional check, Table 1, column (b), reports a regression of the change (first difference) in the COE premium on the changes in the various factors. Among the explanatory variables, only the change in the COE quota is (marginally) significant. These results suggest that changes in COE premia are primarily the result of exogenous factors beyond the control of individual drivers.[7]

– Table 1 here –

3 Behavioral Model

To estimate the impact of sunk costs on car usage and appreciate the corresponding policy implications, we develop a model of driving behavior in the presence of mental accounting. We begin with a model of rational behavior, and then extend the model to include mental accounting for sunk cost. The behavioral model nests the rational model as a special case, and as a consequence, we can empirically test whether the data reject the rational model.

3.1 Rational Behavior

Consider a driver who has just bought a car in period 0. (We focus on individuals who have already bought a car and, by contrast with de Jong (1990), do not model the decision whether to buy a car.) She must decide how many kilometers to drive, q_t, in each month t over a planning horizon, $1, \ldots, T$. In each month, t, let the driver's utility be

$$U(q_t, t) = B(q_t, t) - C(q_t, t) - D(t), \tag{2}$$

where $B(q_t, t)$ is the benefit from usage, $C(q_t, t)$ is usage-related costs other than depreciation, and $D(t)$ is depreciation.

Let the benefit from usage,

$$B(q_t) = \theta_0 + \theta_1 q_t - \theta_2 q_t^2 + \phi(t) q_t, \tag{3}$$

[7]To the extent that congestion affects the COE premium, it is *current* congestion that affects the current COE premium. However, our empirical analysis regresses current usage on the COE premium at the *time of purchase*, which is considerably earlier.

or equivalently the marginal benefit from usage,

$$B'(q_t) = \theta_1 - 2\theta_2 q_t + \phi(t). \tag{4}$$

We assume that $\theta_1, \theta_2, \phi(\cdot) > 0$, and are such that the marginal benefit, $B'(.) > 0$, and the marginal benefit diminishes with usage, $B''(.) < 0$.[8]

The function, $\phi(\cdot)$, represents the effect of time on marginal benefit. The driver's marginal benefit might decline with time for two reasons. One is a taste for novelty – newer cars provide more excitement. The other reason is that older cars break down more frequently, and so, provide less benefit. Consequently, the marginal benefit diminishes with time (or more precisely, age of the car). On the other hand, if the driver needs time to learn about the various features of the car, her marginal benefit might actually increase initially and then decline with time. To allow for both possibilities, we specify that

$$\phi(t) = \phi_1 t + \phi_2 t^2, \tag{5}$$

with no restriction on the signs of ϕ_1 and ϕ_2.

With regard to the cost of usage other than depreciation, we assume that it comprises the perceived cost of gasoline (petrol) and cost of congestion, both of which increase linearly with usage. Specifically,

$$C(q_t, t) = \beta_1 g_t q_t + \beta_2 c_t q_t, \tag{6}$$

where $\beta_1, \beta_2 > 0$. On the right-hand side of (6), $\beta_1 g_t$ represents the perceived cost of gasoline per kilometer of usage, where g_t is the price, and $\beta_2 c_t$ represents the perceived cost of congestion per kilometer of usage, where we measure c_t by the number of cars per kilometer of road.

As for depreciation, referring to the retail price of the car in (1), let

$$P = \text{Retail price} - \text{ARF} - \text{COE premium} = [1 + \pi_{tax}] \cdot \text{OMV} + \text{Retail mark-up}, \tag{7}$$

represent the "ex-policy price" of the car. We assume that the depreciation of the retail

[8]The quadratic functional form, (3), may be interpreted as a Taylor series approximation of a more general benefit function that exhibits diminishing marginal benefit.

price is additively separable in time and usage. Based on the rebate structure of the COE and ARF (described in Section 2 above), we model the depreciation as

$$D(t) = \delta_0[P - s_0] + \delta_1(t)[ARF - s_1] \cdot 1(t > 60) + \delta_2(t)[COE - s_2] \cdot 1(t > 24) + \delta_3 q_t, \quad (8)$$

where s_0, s_1, and s_2 represent the sunk portions of the ex-policy price, ARF, and COE premium, and δ_0 is the depreciation rate of the ex-policy price, $\delta_1(t)$ and $\delta_2(t)$ are the depreciation functions of the ARF and COE premium (as given in Figure 3), and δ_3 is the rate of depreciation with usage.

Substituting above, the consumer's utility is

$$U(q_t, t) = \theta_0 + \theta_1 q_t - \theta_2 q_t^2 + [\phi_1 t + \phi_2 t^2]q_t - \beta_1 g_t q_t - \beta_2 c_t q_t - D(t). \quad (9)$$

Assuming that the driver is forward-looking, in each month, t, she chooses usage, q_t, to maximize the cumulative utility of driving, $\sum_{\tau=t}^{T} U(q_\tau, \tau)$. Proposition 1 characterizes the optimal usage.

Proposition 1 *With rational behavior, the optimal usage in month $t = 1, \ldots, T$ is*

$$q_t^* = \frac{1}{2\theta_2}\left[[\theta_1 - \delta_3] + \phi_1 t + \phi_2 t^2 - \beta_1 g_t - \beta_2 c_t\right]. \quad (10)$$

Proof. In each month t, the consumer chooses q_t to maximize

$$\sum_{\tau=t}^{T} U(q_\tau, \tau) = \sum_{\tau=t}^{T}\left[\theta_0 + \theta_1 q_\tau - \theta_2 q_\tau^2 + [\phi_1 \tau + \phi_2 \tau^2]q_\tau - \beta_1 g_\tau q_\tau - \beta_2 c_\tau q_\tau - D(\tau)\right]. \quad (11)$$

Substituting from (8) and maximizing (11) with respect to q_t, the optimal usage is given by

$$2\theta_2 q_t^* = [\theta_1 - \delta_3] + \phi_1 t + \phi_2 t^2 - \beta_1 g_t - \beta_2 c_t, \quad (12)$$

for all t. [ ]

By Proposition 1, the optimal usage is independent of the sunk costs, s_0, s_1, and s_2, related to the ex-policy price, ARF, and COE premium. It varies with time according to (5) and declines with the costs of gasoline and congestion.

3.2 Mental Accounting for Sunk Costs

Next, we generalize the model to allow for the sunk cost fallacy. Suppose that the driver's utility in month t depends on both usage and mental accounting for the sunk cost in the following way,

$$U(Q_t, q_t, t) = \begin{cases} B(q_t) - C(q_t, t) - D(t) - M(S, Q_t) & \text{if } t \leq T_S \\ B(q_t) - C(q_t, t) - D(t) & \text{if } t > T_S. \end{cases} \tag{13}$$

Within the horizon, $t \leq T_S$, (13) differs from the model of rational behavior by the additional term, $M(S, Q_t)$, which represents the psychological disutility of carrying a mental account of the sunk cost.

Gourville and Soman (1998) and Thaler (1999) find that sunk costs are salient and influence behavior, with diminishing effect, over a finite period. Accordingly, we stipulate that the mental accounting lasts for some finite horizon, T_S. Beyond the horizon, for $t > T_S$, the sunk cost is sufficiently remote that it does not affect the driver, and so, her usage follows the rational model.

Referring to Section 2 and Figure 3, the structure of Singapore government policies suggests that the mental accounting horizon might range between 24 and 60 months. With regard to the COE premium, 20% is non-refundable, while the refundable part declines on a daily basis from the third until the tenth year. So, the non-refundable sunk part of the COE premium is like a lump sum payment for two years, which suggests that drivers might carry a mental account for 24 months. As for the ARF, 25% is non-refundable, while the refundable part declines in steps of 5% each year from the sixth until the tenth year. So, the non-refundable sunk part of the ARF is like paying a lump sum for five years, which suggests that drivers might carry a mental account for 60 months.

We stipulate that the psychological disutility is well-behaved in the following sense: $M(S, Q_t)$ decreases in Q_t, with $\lim_{t \to T_S} M(S, Q_t) = 0$. Under this assumption, the psychological disutility of carrying the mental account diminishes with cumulative usage. Intuitively, as the driver accumulates usage, the sunk cost becomes less salient and its psychological effect wears off.

In order to maintain analytical tractability without loss of generality, we specify the psychological disutility as a linear function of cumulative mileage, sunk cost, and their interaction,

$$M(S, Q_t) = \lambda_1 + \lambda_2 Q_t + \lambda_3 S + \lambda_4 S \cdot Q_t. \tag{14}$$

By assumption, $M(S, Q_t)$ is decreasing in Q_t, which implies that $\lambda_2 + \lambda_4 S < 0$. For this condition to hold with arbitrary sunk costs, we must have $\lambda_4 \leq 0$. In this case, sunk costs affect usage if only if the inequality is strict, i.e., $\lambda_4 < 0$. As we explain below, testing this restriction is the basis of our empirical investigation.

Substituting from (3), (5), (6), (8), and (14) in (13), the driver's utility within the mental accounting horizon, T_S, simplifies to

$$\begin{aligned} U(Q_t, q_t, t) &= \theta_0 + \theta_1 q_t - \theta_2 q_t^2 + [\phi_1 t + \phi_2 t^2] q_t - \beta_1 g_t q_t - \beta_2 c_t q_t \\ &- \left[\delta_0 [P - s_0] + \delta_1(t)[ARF - s_1] \cdot 1(t > 60) + \delta_2(t)[COE - s_2] \cdot 1(t > 24) + \delta_3 q_t\right] \\ &- [\lambda_1 + \lambda_2 Q_t + \lambda_3 S + \lambda_4 S \cdot Q_t]. \end{aligned} \tag{15}$$

Assume that the driver is forward-looking, and, in each month, t, chooses usage, q_t, to maximize $U_t \equiv \sum_{\tau=t}^{T_S} U(Q_\tau, q_\tau, \tau)$. The driver accounts for the effect of q_t on future utility through the cumulative usage up to month t, $Q_t = \sum_{\tau=1}^{t} q_\tau$.

Within the horizon, T_S, we characterize the driver's usage in the last month, $q^*_{T_S}$, and then work backward, solving for $q^*_{T_S-1}$, etc. Specifically, for each $t = T_S, T_S - 1, \ldots, 2, 1$, differentiate U_t with respect to q_t to obtain the first-order condition.

Differentiating the cumulative expected utility for $t = T_S$,

$$\begin{aligned} \frac{dU_{T_S}}{dq_{T_S}} &= \frac{dU(Q_{T_S}, q_{T_S}, T_S)}{dq_{T_S}} \\ &= [\theta_1 - \delta_3] - 2\theta_2 q_{T_S} + \phi_1 T_S + \phi_2 T_S^2 - \beta_1 g_{T_S} - \beta_2 c_{T_S} - \lambda_2 - \lambda_4 S = 0, \end{aligned}$$

and hence,

$$q^*_{T_S} = \frac{1}{2\theta_2}\left\{[\theta_1 - \delta_3] + \phi_1 T_S + \phi_2 T_S^2 - \beta_1 g_{T_S} - \beta_2 c_{T_S} - \lambda_2 - \lambda_4 S\right\}.$$

Similarly, differentiating the cumulative expected utility for $t = T_S - 1$ and simplifying the terms,

$$\begin{aligned}\frac{dU_{T_S-1}}{dq_{T_S-1}} &= \frac{dU(Q_{T_S}, q_{T_S}, T_S)}{dq_{T_S-1}} + \frac{dU(Q_{T_S-1}, q_{T_S-1}, T_S-1)}{dq_{T_S-1}} \\ &= [\theta_1 - \delta_3] - 2\theta_2 q_{T_S-1} + \phi_1[T_S - 1] + \phi_2[T_S-1]^2 \\ & \quad -\beta_1 g_{T_S-1} - \beta_2 c_{T_S-1} - 2\lambda_2 - 2\lambda_4 S \\ &= 0,\end{aligned}$$

and, so, we have

$$q^*_{T_S-1} = \frac{1}{2\theta_2}\Big\{[\theta_1 - \delta_3] + \phi_1[T_S-1] + \phi_2[T_S-1]^2 - \beta_1 g_{T_S-1} - \beta_2 c_{T_S-1} - 2\lambda_2 - 2\lambda_4 S\Big\}.$$

Reasoning recursively, we can show that the optimal usage in month $t = 1, \ldots, T_S$ is

$$q^*_t = \frac{1}{2\theta_2}\Big\{[\theta_1 - \delta_3] + \phi_1 t + \phi_2 t^2 - \beta_1 g_t - \beta_2 c_t - \lambda_2[T_S - t + 1] - \lambda_4[T_S - t + 1]S\Big\}. \quad (16)$$

For months, $t = T_S + 1, \ldots, T$, the optimal usage is characterized by the rational model (10). Accordingly, we have

Proposition 2 *With mental accounting for sunk costs, the driver chooses usage,*

$$q^*_t = \begin{cases} [\theta_1 - \delta_3] + \phi_1 t + \phi_2 t^2 - \beta_1 g_t - \beta_2 c_t & \\ \qquad -\lambda_2[T_S - t + 1] - \lambda_4 S[T_S - t + 1] & \text{if } t \leq T_S \\ [\theta_1 - \delta_3] + \phi_1 t + \phi_2 t^2 - \beta_1 g_t - \beta_2 c_t & \text{if } t > T_S \end{cases} \quad (17)$$

where θ_2 is normalized as $\theta_2 = \frac{1}{2}$.

Notice that, if $\lambda_2 = \lambda_4 = 0$, then (17) simplifies to (10). Hence, the model of mental accounting nests rational behavior as a special case.

To characterize the implications of mental accounting for sunk costs on usage, consider the marginal effect of the sunk cost on the driver's choice of usage. Differentiating (17) with respect to S,

$$\frac{dq^*_t}{dS} = -\lambda_4[T_S - t + 1]. \quad (18)$$

If $\lambda_4 < 0$, then the empirical implication of mental accounting for sunk costs is higher usage at all times, to an extent that diminishes linearly with time. If $\lambda_4 = 0$, then, $dq_t^*/dS = 0$, and the mental accounting for sunk costs has no effect on usage. Thus we have the following corollary.

Corollary 1 *With mental accounting for sunk costs, if $\lambda_4 < 0$, the driver chooses usage, q_t^*, in months, $t = 1, \ldots T_S$, that increases in the sunk cost and attenuates over time at a rate that increases in the sunk cost.*[9]

Figure 5 illustrates the difference in the trajectory of usage with and without mental accounting for sunk costs. Assume that the costs of gasoline and congestion are constant, g_t, c_t are time-invariant, and and that there is no time (age)-dependent marginal benefit, $\phi_1 = \phi_2 = 0$. Then, with rational behavior, the monthly usage would be constant throughout T_S.

– Figure 5 here –

By contrast, comparing (17) with (10), mental accounting for sunk costs would affect behavior in two ways. First, usage increases with the sunk cost (Proposition 2), and second, usage attenuates over time at a rate that increases with the sunk cost (Corollary 1). Figure 5 illustrates the trajectory of usage for two levels of the sunk cost. With a larger sunk cost, the usage would begin at a higher vertical intercept, but slope downward with age of the car at a *faster* rate to end at the same point.

The attenuation of sunk cost is quite intuitive. Consider two persons with the same utility function, and, in particular, the same mental accounting horizon. Suppose that they incur

[9] The model of mental accounting encompasses a more specific model of amortization that we presented in an earlier version. Under the assumptions presented in the earlier version, the driver amortizes the burden of the sunk cost by the accumulated usage relative to some target, $\hat{Q}$, for cumulative usage at the end of the mental accounting horizon. At each point in time, the more that the driver has used the car up to then, the lower is the mental burden of the sunk cost. Formally, in $M(S, Q_t)$, the interaction between sunk cost and cumulative usage is

$$\lambda S \cdot \left[1 - \frac{Q_t}{\hat{Q}}\right] = \lambda S - \frac{\lambda}{\hat{Q}} S Q_t. \tag{19}$$

Referring to (14), this theory predicts that $\lambda_4 = -\frac{\lambda}{\hat{Q}} < 0$, and, so, by the Corollary, usage increases in the sunk cost but attenuates over time at a rate that increases in the sunk cost.

different sunk costs in buying cars. The sunk cost fallacy would induce both persons to drive more than rationally, to a larger extent for the individual who incurs the larger sunk cost. Over time, with accumulated driving, the burden of mental accounting dissipates and the additional higher-than-rational driving induced by the sunk cost fallacy diminishes to zero as the drivers approach the mental accounting horizon. Since the horizon is the same for both individuals, the rate of attenuation is faster for the person who incurred the larger sunk cost.

The effect of the sunk cost on the rate of attenuation of usage over the life of the car is the essence of our empirical strategy. This effect on attenuation distinguishes the model of mental accounting for sunk costs from the most obvious alternative explanation of any empirical relation between usage and sunk costs, which is selection (called "screening" by Ashraf et al. (2010)). Selection causes higher sunk costs to be associated with higher usage in the following way. When COE premia and ARF are higher, the prices of new cars would be higher. With the increase in price, people who plan to drive less would be less likely to buy cars, and so, the population of car owners would comprise relatively more intensive drivers.

An increase in usage with respect to the price of the car may be associated with mental accounting for sunk costs or with selection. However, there is no reasonable explanation for why the effect of selection should attenuate over the life of the car. By contrast, our behavioral model specifically implies that, with mental accounting for sunk costs, the effect of the sunk cost should attenuate over time and therefore affect the rate at which usage attenuates over time.[10]

Corollary 1 implies that the effect of the sunk cost attenuates with time. The essential reason is the structure of the mental accounting. Referring to (14), in each month, as the driver looks forward, the mental burden of the sunk cost is reduced by some extent due to cumulative usage. In the earlier months, the weight of the mental account is large and therefore the impact on usage is large. By contrast, mental account in the periods close to the terminal month is progressively less, and the impact on usage diminishes gradually. Accordingly, it is optimal for the driver to use the car relatively more in the earlier months

[10]In the Appendix, we provide a simple formalization of the difference between selection and attenuation due to the sunk cost fallacy.

to the extent that the sunk cost is larger.

This theoretical implication is consistent with two previous empirical studies. In the experiment by Arkes and Blumer (1985: 128), consumers who paid a higher price for the season ticket attended more shows in the first half of the season, but not in the second half. Gourville and Soman (1998: 169-172) monitored attendance at an athletic facility by members who paid for a one-year membership in two semi-annual installments. Members visited the facility most during the month of paying the installment, and their visits declined with each succeeding month. Both studies found that the sunk cost fallacy affected behavior only for finite period of time.

4 Empirical Strategy

To set up the econometric model for structural estimation, let the actual usage of individual driver i in month t (or more precisely, the age of the car in months) be $q_{it} = q^*_{it} + \epsilon_{it}$, where ϵ_{it} is an error. Substituting from (17) for q^*_{it},

$$\begin{aligned} q_{it} \;&=\; [\theta_1 - \delta_3] - \lambda_2[T_S - t + 1] \cdot 1_{t \leq T_S} + \phi_1 t + \phi_2 t^2 - \beta_1 g_t - \beta_2 c_t \\ &\quad - \lambda_4[T_S - t + 1] S_i \cdot 1_{t \leq T_S} + \epsilon_{it}, \end{aligned} \tag{20}$$

for $i = 1, \dots, N$.

Assume that the error, ϵ_{it}, comprises two elements,

$$\epsilon_{it} = \xi_i + \nu_{it}, \tag{21}$$

where ν_{it} is pure individual and time specific idiosyncratic error, and ξ_i is an individual fixed effect that captures all unobservable time-invariant attributes of the owner that may influence usage. The individual fixed effect controls for differences including selection by driving intensity, for instance, when higher car prices selectively screen out those who plan to drive less intensively. The individual fixed effect also controls for differences between first and second cars. Two-car households would drive each car less than one-car households.[11]

[11]Empirically, the retail price of cars fell from 2000 to 2009, and then rose again. As car prices

Our data on car usage is based on periodic services of each car at irregular time intervals. To apply the econometric model, we organize the data as monthly averages between service visits. Suppose that car i was serviced in months, t_{ir}, where $r = 1, 2, \ldots, R$, and $t_{i0} = 0$. Then, define the inter-service average of usage,

$$q_{ir} \equiv \frac{1}{t_{ir} - t_{i,r-1}} \sum_{\tau=t_{i,r-1}+1}^{t_{ir}} q_{i\tau}, \tag{22}$$

the inter-service average of the remaining horizon, inter-service average of the age of the car, and the inter-service average of the square of the car age,

$$\begin{aligned} m_{1,ir} &\equiv \frac{1}{t_{ir} - t_{i,r-1}} \sum_{\tau=t_{i,r-1}+1}^{t_{ir}} [T_S - \tau + 1] \cdot 1[\tau \le T_S], \qquad (23) \\ m_{2,ir} &\equiv \frac{1}{t_{ir} - t_{i,r-1}} \sum_{\tau=t_{i,r-1}+1}^{t_{ir}} \tau, \\ z_{ir} &\equiv \frac{1}{t_{ir} - t_{i,r-1}} \sum_{\tau=t_{i,r-1}+1}^{t_{ir}} \tau^2. \end{aligned}$$

Likewise, define the inter-service averages of the cost of petrol, congestion, and idiosyncratic error,

$$g_{ir} \equiv \frac{1}{t_{ir} - t_{i,r-1}} \sum_{\tau=t_{i,r-1}+1}^{t_{ir}} g_\tau, \;\; c_{ir} \equiv \frac{1}{t_{ir} - t_{i,r-1}} \sum_{\tau=t_{i,r-1}+1}^{t_{ir}} c_\tau, \;\; \nu_{ir} \equiv \frac{1}{t_{ir} - t_{i,r-1}} \sum_{\tau=t_{i,r-1}+1}^{t_{ir}} \nu_{i\tau}. \tag{24}$$

Substituting the above and (21) in (20),

$$q_{ir} = [\theta_1 - \delta_3] - \lambda_2 m_{1,ir} + \phi_1 m_{2,ir} + \phi_2 z_{ir} - \beta_1 g_{ir} - \beta_2 c_{ir} - \lambda_4 S_i m_{1,ir} + \xi_i + \nu_{ir}, \tag{25}$$

for $r = 1, 2, \ldots, R$. To abstract from the individual fixed effect, we recast the model in first differences, which yields the following estimation model,

$$\Delta q_{ir} = -\lambda_2 \Delta m_{1,ir} + \phi_1 \Delta m_{2,ir} + \phi_2 \Delta z_{ir} - \beta_1 \Delta g_{ir} - \beta_2 \Delta c_{ir} + \lambda_4 S_i \Delta m_{1,ir} + \Delta \nu_{ir}, \tag{26}$$

fell, some households may have purchased a second car, and so, with two cars, would use each car relatively less, thus, giving rise to a correlation between lower car prices and less usage of each car.

where $\Delta q_{ir} \equiv q_{ir} - q_{i,r-1}$, $\Delta m_{1,ir} \equiv m_{1,ir} - m_{1,i,r-1}$, $\Delta m_{2,ir} \equiv m_{2,ir} - m_{2,i,r-1}$, $\Delta z_{ir} \equiv z_{ir} - z_{i,r-1}$, $\Delta g_{ir} \equiv g_{ir} - g_{i,r-1}$, $\Delta c_{ir} \equiv c_{ir} - c_{i,r-1}$ and $\Delta \nu_{ir} \equiv \nu_{ir} - \nu_{i,r-1}$.

5 Data

Our primary source of data is the authorized dealer for a mid-market brand of cars in Singapore. The dealer provided the complete service records of all new cars sold between 2000-2013 under a non-disclosure agreement for this study. The cars are different models of the same brand.

Owners bring their cars to the authorized dealer for maintenance service. The service records for each car include the date of registration, engine size, service dates, and odometer readings. To protect customer confidentiality, the dealer did not provide any demographic information on the car buyers.

In our sample, the maximum observed age is 119 months, which is less than the lifespan of a COE (120 months). To exclude outliers, we further limited the sample to cars with usage within 2 standard deviations of the logarithm of the average monthly usage. After cleaning for obvious recording errors (mainly cars with odometer readings that decreased over time), excluding cars that were defective (identified by premature service visits), and cars with fewer than 4 service records, the final sample comprises 8,264 cars with 45,195 service visits.[12]

The cars were purchased at different times, the owners perform maintenance at varying intervals, and, so, the cars have different numbers of service visits. Accordingly, the data constitute an unbalanced panel of cars with average monthly usage ranging between 539 and 4,189 kilometers (or equivalently, annual usage ranging between 4,043 and 31,418 miles).[13]

Our next source of data is the Land Transport Authority (LTA). The LTA collects and publishes the retail price, OMV, ARF, and COE for each brand and model of car on a monthly basis. We match this information by month and engine size to the registration of

[12]The Supplement reports an estimate based on the larger sample of cars with usage within 3 standard deviations of the average, which sample comprises 8,401 cars with 45,620 observations.

[13]The Supplement also reports estimates based on a smaller sample that includes all observations on cars with average monthly usage up to 3,000 kilometers per month.

each car. To represent the price of gasoline, we use the Consumer Price Index (CPI) of 98 octane petrol, and to represent traffic congestion, we use the number of cars (published monthly) divided by the quantity of road space in kilometers (published annually).

Table 2 reports summary statistics of the data. Average monthly usage in the sample is 1,545 kilometers. The retail price of the cars ranges between S$110,000 and S$317,405 with an average of S$176,625 (equivalent to US$114,692), while the average ARF and COE premium are S$47,207 and S$26,820 respectively. So, the ARF and COE contribute about 42% of the retail price. The gasoline price index increased from around 69 in 2000 to 131 in 2013. Over the same period, the level of congestion rose from about 83 to over 106 cars per kilometer of road.

– Table 2 here –

6 Results

The model of mental accounting (Corollary 1) predicts that monthly usage attenuates over time if $\lambda_4 < 0$. Figure 2 provides some coarse evidence of such attenuation. By (14), this means that the burden of the sunk cost diminishes with cumulative usage, which is consistent with a behavioral model of mental accounting in which car buyers mentally amortize the sunk cost relative to some target cumulative usage.

An obvious threat to our empirical strategy is the close correlation between the retail price and sunk cost. Hence, any correlation between monthly usage and sunk cost as depicted in Figure 1(B), may well be due to selection among car buyers. For instance, when COE premia and car prices are high, only people who plan to drive intensively will buy cars, and hence, usage will be correlated with car prices, and so, correlated with sunk costs.

To check in a simple way, Figure 6 presents locally weighted polynomial regressions of cumulative usage up to 3, 4, and 5 years on the retail price and policy-related sunk costs. Panel (A) suggests that cumulative usage and retail price tended to covary, but the relation is not monotone. By contrast, in panel (B), there seems to be a clear monotone relation between cumulative usage and the policy-related sunk cost (sunk portion of COE premium and ARF).

– Figure 6 here –

To delve further, we use least squares to regress the change in average monthly usage between successive service visits on the retail car price and sunk cost. As (26) shows, casting the estimation model in terms of the change in usage over time removes the individual fixed effect, and so, abstracts from any non-time-varying selection among car buyers. This also means that the effect of the sunk cost, which does not vary with time, can only be identified through interaction with some time-varying factor. Figure 2 suggests that the effect of sunk cost on usage varies with the age of the car.

Table 3 reports the estimates. As Table 3, column (1), reports, the coefficient of the retail price interacted with age of car is negative and significant. Next, in column (2), we break down the retail price into the ex-policy price and the two policy-related sunk costs. The coefficient of the COE-related sunk cost interacted with age of car is negative and significant. Finally, in column (3), we break down the retail price into the ex-policy price and the combined COE and ARF sunk costs. The coefficient of the policy related sunk costs is also negative and significant.

– Table 3 here –

Overall, the evidence presented in Figure 6 and Table 3 is consistent with our behavioral model of mental accounting, specifically, Corollary 1 with $\lambda_4 < 0$. Drivers use their car according to the sunk cost of purchase, and usage attenuates with age of the car at a rate that increases with the sunk cost, and, in particular, the part related to the COE premium.

While suggestive, Figure 6 and Table 3 are reduced form analyses that may not allow counter-factual policy and managerial analyses (furthermore, Figure 6 does not account for selection). Accordingly, we now turn to structural estimation of the behavioral model, (26). Although the data set comprises 45,195 service records, after first-differencing, the estimation sample comprises 36,931 observations.

First, to provide a point of reference, we estimate the rational model, i.e., assuming that $\lambda_2 = \lambda_4 = 0$. The coefficient of the perceived price of gasoline, β_1, is positive and significant. This is consistent with the intuition that higher fuel cost would decrease usage. The coefficient of the perceived cost of congestion, β_2, is positive and also significant.[14]

[14]In the empirical model, (20), the coefficients of gasoline price and congestion are specified as

Regarding the effect of car age on usage, ϕ_1 is positive and significant, while ϕ_2 is negative and significant. The estimated coefficients suggest that the effect of "novelty" is to increase usage over the first 66 months, and decrease thereafter.

Next, we turn to estimate the behavioral model. Recall from (7) that the retail price comprises the ex-policy price, COE premium, and ARF. By government design (Figure 3), elements of the COE premium and ARF are sunk according to specified schedules. Further, just as in any other car market, part of the ex-policy price may be sunk. Accordingly, we generalize (26) to distinguish the policy-related sunk cost, with coefficient, λ_{41}, and the ex-policy price, with coefficient, λ_{42}.

Another issue is the length of the mental accounting horizon. Above, in developing the behavioral model, we inferred from the structure of the COE and ARF refunds that the mental accounting horizon might range between 2 to 5 years. Accordingly, we estimated the model at various horizons, and in Table 4 we report structural estimates of the behavioral model for the horizons of between 24 and 72 months.

– Table 4 here –

The estimates for 24 to 72 month horizons are consistent in several ways – the coefficients of the perceived costs of gasoline and congestion are positive and significant, the coefficients of age and age-squared are positive and negative respectively, and both are significant. The coefficient of the policy-related sunk cost is negative and precisely estimated, and interestingly, the magnitude of the coefficient declines with length of the horizon. The coefficient of the ex-policy price is not significant.

Recall that the rational model is the model of mental accounting subject to the restriction that the coefficients of the sunk costs and the remaining horizon be zero, $\lambda_2 = \lambda_{41} = \lambda_{42} = 0$. Table 4 reports F-tests of these restrictions. Across all horizons, the F-statistics suggest rejection of the null hypothesis that $\lambda_2 = \lambda_{41} = \lambda_{42} = 0$. Apparently, the mental accounting parameters are significant.

The general picture is that, empirically, driving was sensitive to gasoline prices, congestion, and novelty, and, importantly, sensitive to the sunk cost within a mental accounting horizon of 24 to 72 months. Referring to Corollary 1, our results are consistent with $\lambda_4 < 0$

$-\beta_1$ and $-\beta_2$ respectively. Hence, if $\beta_1 > 0$ and $\beta_2 > 0$, then driving decreases with the price of gasoline and congestion.

and a trajectory of higher-than-rational usage that attenuates at a rate that increases with the sunk cost. Our results suggest that car buyers did mentally account for the sunk elements of the ARF and COE premium.

Among the alternative horizons, we prefer 48 months (Table 4, column (d)). This fits between the horizons of 2 to 5 years that we intuitively expect from the structure of the COE and ARF rebates. Statistically, this specification yields the best fit (largest R^2 and log likelihood).

With a 48-month mental accounting horizon, the coefficient of the mental accounting of the policy-related sunk costs, $\lambda_{41} = -0.185$ (s.e. 0.058), is negative and precisely estimated. To interpret this coefficient, we compute the elasticity of usage with respect to the sunk cost as being 0.050 (s.e. 0.016).[15] To gauge the significance of this estimate, consider the increase in the average policy related sunk cost by S$13,038 from S$11,278 to S$24,316 between January 2009 and June 2013, mainly due to an increase in COE premium. Using our estimated elasticity, this increase in sunk cost would be associated with an increase in usage by 5.8% or 90 kilometers a month.[16]

We believe that the actual effect of the sunk cost exceeds this estimate. Drivers would respond to the sunk cost by varying their discretionary driving (their non-discretionary driving – commuting to work and sending children to school – would respond less). The effect of the sunk cost would be larger if it is expressed as a proportion of the discretionary driving. Moreover, our estimate of the effect of sunk cost on car usage did not control for income effects. An increase in the COE or ARF would reduce the buyer's discretionary income, and so, lead to a reduction in all consumption, including driving (Thaler 1980: 49-50). Accordingly, our estimate of the sunk cost effect is conservative.

[15] Consider an increase in the policy-related sunk cost, $0.25 \times ARF + 0.2 \times COE$, by S$10,000. This would increase usage over a planning horizon of 48 months, with a larger increase in usage in the earlier months and smaller increase in usage in the later months. By Table 4, column (d), $\lambda_{41} = -0.185$, so, the total increase in usage would be $-\lambda_{41} \cdot \sum_{t=1}^{48} [48 - t + 1] = 2{,}176$ kilometers over 48 months, which amounts to an average of 45.3 kilometers a month. (Note that, in the estimating equation, the costs and price are measured in millions of Singapore dollars and usage measured in thousands of kilometers.) Dividing by the average monthly usage over the first 48 months, 1550 kilometers, the proportionate change is 45.3/1550. Dividing by the average sunk cost, S$17,150, the proportionate change in the sunk cost is 10/17.5. Hence, the elasticity is 0.050.

[16] Our estimates are based on the normalization $\theta_2 = 1/2$. The estimated coefficients would change with the normalization, but the counterfactual effects would remain the same as the estimated coefficients adjust accordingly.

6.1 Heterogeneous Effects

Table 5 presents additional estimates to explore heterogeneous effects, by size of car and structure of government policy, and to check the sensitivity of our findings to alternative specifications of sunk costs and COE salience. For convenience, Table 5, column (a), reproduces the preferred estimate from Table 4, column (d).

– Table 5 here –

Small/Large Cars

We first explore differences in the effect of sunk costs on driving between large and small cars. The estimate in Table 5, column (b), allows the effect of policy-related sunk costs to vary between small and large cars. The cars in our sample divided roughly equally into two segments at the engine size of 2000 c.c. Since prices correlate with engine size, the division between small (below 2000 c.c.) and large cars (above 2000 c.c.) roughly divides less and more expensive cars. The engine sizes of the vast majority of cars in our sample are clustered around 1800-2000 c.c. and 2400-2600 c.c.

Evidently, the effect of sunk costs on usage was similar among drivers of both small and large cars. The coefficient of the policy-related sunk cost among drivers of small cars is slightly larger than that among drivers of large cars. To investigate further, we estimate (26) separately on the sub-samples of small and large cars, allowing all coefficients to differ between small and large cars. The estimates, presented in Table 5, columns (c) and (d), reveal interesting contrasts. The effect of the policy related sunk cost and the novelty effect are similar among drivers of both types of cars. However, small car owners seem to be sensitive to gasoline price and congestion, whereas drivers of large car are not. This is intuitive, since buyers of large cars are probably better off, and so, would be less sensitive to the relatively minor cost of gasoline.[17]

COE/ARF Sunk Costs

The government discourages car buying through two policies – COE and ARF. Each policy embeds sunk costs but with different time profiles (Figure 3). Car buyers might perceive

[17]By contrast with the preferred estimate for all cars and the estimate for smalle cars, the coefficient of the ex-policy price is significant in the estimate for large cars. Perhaps this is related to the slight difference in the novelty effects between small and large cars.

the sunk costs related to the COE and ARF differently. To investigate, we estimate a specification that allows these two sources of sunk cost to separately affect driving. Following the structure of government policy, we stipulate the COE-related sunk cost to be effective until the 24th month, and ARF-related sunk cost to be effective until the 60th month. As Table 5, column (e), reports, the COE-related sunk cost seems to loom larger in drivers' minds than the ARF-related sunk cost. One possible reason is publicity of the twice-monthly COE auctions, which might remind car owners of the COE-related sunk cost. The estimated elasticity of driving with respect to the COE-related sunk cost is 0.059 (s.e. 0.006).

6.2 Robustness

Empirically, we find that usage attenuates with age of the car at a rate that increases in the sunk cost and interpret this relation in terms of mental accounting for sunk costs. Next, we check the sensitivity of our findings to alternative specifications of sunk costs.

Salience

Twice a month, the government conducts auctions of COEs, which are widely reported in the news media. The current COE premium might influence car owners in their driving. Specifically, to the extent that the current COE premium is less than the COE premium that they paid, car owners might perceive the COE premium to be more salient and drive more. As reported in Table 5, column (f), the inclusion of this variable (the difference between COE premium paid and current COE premium) magnifies the effect of the policy-related sunk cost. The elasticity with respect to the policy-related sunk cost increases is 0.077 (s.e.0.018).[18]

Retail Price

Finally, the structure of the ARF and COE rebates is quite complex. What if car buyers do not understand these intricacies, and perceive the sunk cost to be simply some function of

[18]The higher elasticity compared with the preferred estimate may be related to the coefficient of difference between COE premium paid and current COE premium being positive and significant. This additional variable embeds the COE premium paid with a positive coefficient. Hence, statistically, the additional variable might cause the coefficient of the policy-related sunk cost (which embeds the COE premium paid) to become more negative.

the retail price? To address this concern, we conduct a robustness check with the sunk cost specified simply as a proportion of the retail price,

$$S_i = \rho \cdot \text{Retail price}_i. \tag{27}$$

Estimation of model (26) identifies the product, $\lambda_4 \rho$, but cannot separately identify λ_4 and ρ. As Table 5, column (g), reports, the estimated coefficient of $\lambda_4 \rho$ is negative and significant, and the implied elasticity is 0.073 (s.e. 0.020). This elasticity measures the proportionate change in driving in response to changes in the retail price, and so, is not directly comparable to the elasticity based on the preferred estimate, which measures the proportionate change in driving in response to changes in the policy-related sunk cost. The preferred estimate seems more persuasive – it explicitly provides for the policies (COE and ARF) and the ex-policy price (the retail price less COE premium and ARF) to have different effects, and shows that only the policy-related sunk costs affect driving.

Other Robustness Tests

The Supplement reports additional tests to check the robustness of our findings to differences in sample – limiting to cars more than three years old, including outliers, and limiting to cars with monthly usage of less than 3,000 kilometers. In all robustness checks, usage increases with the policy-related sunk cost.

6.3 Selection

As discussed above, an obvious challenge to our interpretation of the relation between the attenuation of usage and the sunk cost is some form of selection. The econometric model, (26), is cast in terms of first differences of usage, rather than the levels of usage. Differencing wipes out any heterogeneity among car buyers that does not vary with usage or age of the car. Hence, any alternative explanation in terms of selection must involve a correlation between the policy-related sunk costs and attenuation in usage.

Below, we consider alternative ways to explain the correlation between sunk costs and the rate of attenuation of usage. The alternative explanations involve selection related to usage. We conclude that our findings are robust to these alternative explanations.

Demand Shocks

One possible explanation of the correlation between the rate of attenuation of usage and sunk costs arises from exogenous temporary shocks in the demand for driving. Suppose that the demand is random. When the retail price is high, only individuals subject to large positive shocks buy cars. When the retail price is low, all individuals, whether subject to small or large positive shocks, buy cars. Over time, driving reverts to the mean. Then, there will be more attenuation with age among cars bought at higher retail prices (which imply higher policy-related sunk costs).

Our estimates of the behavioural model provide evidence against this demand shock theory. As Table 4 reports, driving was only related to the policy-related sunk cost and not to the ex-policy price. By the demand shock theory, driving should be related to the retail price, and so, to both the policy-related sunk cost and the ex-policy price.

To test the demand shock theory in another way, we draw a specific implication of the hypothesis. The persons buying cars due to large positive shocks would experience a bigger decline in usage as their need for driving reverts to the mean. To the extent that they understand that the shocks are temporary, they should be more likely to sell their cars as their driving decreases.

Our dataset does not include explicit information on changes of ownership. We infer that a car was sold if it was not serviced in the last 12 months of the sample period (July 2013-June 2014), while treating cars serviced during the last 12 months as censored observations.[19] Table 6 reports estimates of the likelihood of sale using the Cox proportional hazard regression. The regression includes one observation for each car, and so, cannot include car fixed effects. To control for non-time varying differences between cars, we include fixed effects for year of registration and engine size. As an additional control, we include cumulative mileage and its square as the likelihood of selling a car might be affected by usage.

As Table 6 reports, the duration of ownership is not significantly related to the retail price, COE premium, ARF, or policy-related sunk costs (to facilitate interpretation, the Table presents the estimated coefficients rather than hazard ratios). These estimates suggest that large demand shocks and mean reversion probably do not explain the faster attenuation of driving among buyers who incurred larger policy-related sunk costs.

[19]Our dataset of service ends in June 2014.

– Table 6 here –

Differential Breakdown

Yet another subtle alternative explanation of the correlation between the rate of attenuation of usage and sunk costs arises from differential breakdowns. When car prices (and policy-related sunk costs) are high, the people who buy cars are those who plan to drive more intensively. The more intense driving wears out their cars, causing more frequent breakdowns, which results in faster attenuation of driving.

The differential breakdown theory implies that the cars bought when retail prices are high would be serviced more frequently. To investigate, we analyze the number of services over the life of the car. Under the alternative explanation, cars purchased at higher prices should undergo more services. Since the number of service visits is a count variable, we apply a Poisson regression. The regression includes one observation for each car. To control for non-time varying differences between cars, we include fixed effects for year of registration and engine size. As additional controls, we include cumulative mileage and age at last service and their squares as the number of services would accelerate with usage and age.

– Table 7 here –

Table 7 presents the estimates and, for easy interpretation, reports marginal effects rather than coefficients. Referring to Table 7, column (a), the marginal effect of the price is not significant. Breaking down the retail price, Table 7, column (b), shows that the number of services is not significantly related to the ex-policy price, COE premium, or ARF. Table 7, column (c), shows that the number of services is not significantly related to the policy-related sunk cost. It is somewhat puzzling that the number of services is positively related to the ex-policy price. We do not have a good explanation of this phenomenon. Nevertheless, it does not affect our inference that the relation between attenuation of usage and sunk costs is not explained by differential breakdowns.

7 Hong Kong Drivers

To provide a comparative analysis, we procured information on the same brand of cars for 962 cars sold between 2001 and 2013 in Hong Kong. We first qualify that the Hong Kong analysis might be less reliable than the Singapore analysis, which is based on a larger sample, more precise data on prices, and most importantly, a government policy that clearly specifies the sunk costs.

Singapore and Hong Kong are quite similar – both are densely populated with a substantial middle class, are highly urbanized, and their roads are subject to congestion. Hong Kong imposes an one-off registration tax, which presently ranges from 40 to 115 percent, but does not limit the sales of new cars (no COE system or equivalent). Hence, buying a new car in Hong Kong does not involve any policy-induced sunk cost. The only possible sunk cost is, as in most other countries, that related to the retail price.

Unlike Singapore, the government of Hong Kong does not publish the wholesale cost or retail price of cars. We assume that the wholesale cost is the same in Hong Kong and Singapore, which is reasonable, as both cities are major ports quite distant from the source of the cars. We procure the retail prices for several years, and use the wholesale cost to impute the retail margin in Hong Kong, and then apply the same retail margin to calculate the retail prices in other years.

Table 8 reports summary statistics of the Hong Kong data. The sample is much smaller, partly due to the population of cars in Hong Kong being about one-third smaller than in Singapore (in 2007, the number of private cars was 372,203 in Hong Kong as compared with 571,041 in Singapore) and partly due to incomplete data. Average monthly usage is 1,106 kilometers, which is about one-quarter lower than in the Singapore sample, while the average car is 50.8 months old, which is about the same as in the Singapore sample.

– Table 8 here –

The big difference between the two markets is in the retail price of cars. The retail price in the Hong Kong sample ranges between HK$240,900 and HK$793,800, with an average of HK$514,300 (equivalent to US$65,900), which is about 40% less than the Singapore average price. The index of gasoline prices rose from 73.6 in June 2001 to 123.9 in April 2013, while, over the same period, the level of congestion rose from about 95.4 to almost 116.2 cars per kilometer of road. Referring to Figure 7, we note attenuation in usage with age of the car and faster attenuation among cars for which prices were higher.

– Figure 7 here –

Table 9 presents the estimates of the behavioral model of mental accounting for the Hong Kong drivers. As a baseline, Table 9, column (a), reports the estimate of the rational model. The coefficient of age, ϕ_1, is negative and significant, while the coefficient of the square of age, ϕ_2, is not significant. This suggests that, among Hong Kong car buyers, the novelty effect kicks in without delay. In addition, the estimates suggest that gasoline prices do not affect usage significantly, although congestion does.

– Table 9 here –

By contrast with Singapore, the government of Hong Kong does not apply any policy that embeds sunk costs within specific horizons. So, we estimate the behavioural model for alternative horizons, and find that the effect of sunk costs is insignificant for horizons exceeding 36 months. However, there is significant evidence of the sunk cost fallacy for horizons of between 20 and 36 months. For all horizons, the coefficient of the retail price, $\rho\lambda_4$ is negative and significant, and the F-test of the restrictions, $\lambda_2 = \lambda_4 = 0$, can be rejected. Hence, the estimates suggest that drivers were influenced by sunk costs.

We treat these estimates with caution as they are less precisely estimated due to the small sample. Subject to that proviso, we focus on the 20-month horizon (Table 9, column (b)), which generates marginally higher R^2 and log likelihood. The coefficient of the retail price, $\rho\lambda_4 = -0.023$ (s.e. 0.006), is negative and precisely estimated. This implies that the elasticity of usage with respect to the retail price is 0.099 (s.e. 0.026). The equivalent estimate for the Singapore drivers (Table 5, column (g)) generates an estimated elasticity of 0.073 (s.e. 0.020), which is not significantly different.

Overall, we infer that the estimates with Hong Kong data suggest that sunk costs related to the retail price do influence car buyers to increase driving. The mental accounting horizon is shorter than that among Singapore drivers, and the elasticity of driving with respect to the retail price is similar.

8 Implications for Public Policy and Management

Our findings of the sunk cost effect have implications for both public policy, particularly, with respect to management of road congestion, and pricing of durable goods. The Singapore government manages traffic congestion through pricing of road usage and limiting car ownership. By design, the Additional Registration Fee (ARF) and Certificate of Entitlement (COE) embody substantial sunk costs. Our results suggest that these sunk costs resulted in the unintended consequence of stimulating driving (among those who did buy a car).

Between January 2009 and June 2013, the Singapore government reduced the relevant quota of COEs by 10,484 from 17,030 to 6,546. The quota reduction coupled with growth of the Singapore economy resulted in the policy-related sunk cost rising by S$13,037 from S$11,278 to S$24,316. Using our preferred estimate, this increase in the sunk cost would be associated with an increase in monthly usage by 5.8% or 90 kilometers a month.

Hence, absent any other policy changes, the reduction in the COE quota would have affected the road usage in two ways. Based on the average driving in our sample, the reduction in the number of cars would have reduced driving (as the government intended) by 16.2 million kilometers a month. On the other hand, mental accounting for sunk costs would have produced a countervailing effect. Based on our preferred estimate, the concomitant increase in the COE premium would have been associated with an increase in driving (which the government did not intend) by 0.9 million kilometers a month.

Indeed, the Singapore government perceives that sunk costs significantly affect driving:

> "because sunk costs matter, the high fixed cost [sic] of car ownership can be inimical to our objective of restraining car usage. Thus, instead of simply relying on high car ownership cost to manage congestion on the road, the Government has been reducing vehicle taxes and shifting more towards usage charges (through the ERP) to manage the demand for road space" (Leong and Lew 2009).[20]

If managers are influenced by sunk costs, our results have implications for the pricing of durable goods such as enterprise software, manufacturing equipment, and printers. For example, producers of enterprise software such as Oracle and SAP sell systems and then also sell complementary post-sale services to their installed base of customers. Similarly,

[20]Leong and Lew (2009) mistook "sunk costs" as being synonymous with "fixed costs". See, for instance, Png (2012: 119-120) for the distinction between sunk and fixed costs. "ERP" refers to electronic road pricing, the Singapore government system that charges for use of roads by day of the week and time of the day.

manufacturers such as Tetrapak and Hewlett-Packard sell machinery and then also sell consumables to buyers of their equipment.

The "razor-blade" model suggests setting a low price for the platform to entice customers, and then setting higher prices on the complementary consumable to earn profits. By contrast, our findings suggest that the vendor ought to price the platform relatively high, so that the buyer will feel a need to mentally account for the sunk cost of the purchase and hence step up purchases of the consumable. This implication resonates with the previous literature on mental accounting (Thaler 1990: 49-50).

9 Concluding Remarks

In this paper, we investigate the effect of sunk costs on usage of a durable good. First, we develop a behavioral model that incorporates mental accounting for sunk costs which nests rational behavior as a special case. In the context of car usage, we characterize the optimal dynamic driving behavior and how sunk costs might affect driving with age of the car.

Then, we take the model to a proprietary panel data-set of 8,264 cars between 2000-2013 in Singapore. Through structural estimates, we find compelling evidence of the sunk cost fallacy. People who incurred larger sunk costs in buying cars drove more and their driving attenuated with age of car relatively faster. This effect of sunk costs was significant in the first 48 months of car ownership and was stronger among buyers of small cars. Our results are robust to various checks including alternative explanations in terms of selection, the specification of sunk costs, and salience of sunk costs. We also estimated the behavioral model on a Hong Kong dataset and found similar results.

Our empirical finding suggests that individuals do not fully self-correct the effect of sunk costs on decision-making even in a repeated situation. While our main analysis is based on Singapore data, the Hong Kong analysis suggests that the effect of sunk costs on car buyers is more widespread. Our estimates suggest that usage of durable goods increases with the sunk element of the price and attenuates over some horizon, and that the rate of attenuation increases with the sunk cost.

By contrast with our results, in field experiments, Ashraf et al. (2010) and Cohen and

Dupas (2010) found no effect of price paid on consumer behavior. The disparity in findings may be due to differences in context. We investigate continuing usage of an expensive high-involvement durable rather than a one-off purchase. The limitation of our study is that it is observational, being based on actual behavior in response to changes in sunk costs due to continuing government policy. Since there is no random assignment of sunk costs to different individuals, we cannot completely rule out the apparent sunk cost effect being due to some unobserved factor.

In future research, it would be good to investigate the factors that influence the sunk cost effect and how individuals differ in their sensitivity to sunk costs. Are consumers more sensitive to sunk costs where the stakes are larger and in a repeated situation, as suggested by the difference between our results and those of Ashraf et al. (2010) and Cohen and Dupas (2010)? Besides duration of time, what other factors can amplify or diminish the effect of sunk costs on decision-making? Can customers learn to overcome the effect of sunk costs? If so, what debiasing techniques will be most effective?

The answers to these questions would help policy-makers, managers, and consumers to correct sunk-cost bias and make more effective decisions across multiple contexts – public policy, management of businesses and organizations, and personal choice.

References

[1] Arkes, Hal R., and Catherine Blumer, "The psychology of sunk cost", *Organizational Behavior and Human Decision Processes*, Vol. 35, No. 5, December 1985, 124-140.

[2] Ashraf, Nava, James Berry, and Jesse S. Shapiro, "Can Higher Prices Stimulate Product Use? Evidence from a Field Experiment in Zambia", *American Economic Review*, Vol. 100 No. 5, 2010, 2382-2413.

[3] Baliga, Sanjeev, and Jeffrey. C. Ely, "Mnemonomics: The Sunk Cost Fallacy as a Memory Kludge", *American Economic Journal: Microeconomics*, Vol. 3 No. 4, November 2011, 35-67.

[4] Barron, Jack M., Dmitry V. Chulkov, and Glen R. Waddell, "The escalation phenomenon and executive turnover: Theory and evidence", Mimeo, Purdue University, 2001.

[5] Camerer, Colin F., and Robert A. Weber, "The econometrics and behavioral economics of escalation of commitment: a re-examination of Staw and Hoang's NBA data", *Journal of Economic Behavior & Organization*, Vol. 39, No. 1, 1999, 59-82.

[6] Cohen, Jessica, and Pascaline Dupas, "Free Distribution or Cost-Sharing? Evidence from a Randomized Malaria Prevention Experiment", *Quarterly Journal of Economics*, Vol. 125 No. 1, February 2010, 1-45.

[7] de Jong, G.C., "An Indirect Utility Model of Car Ownership and Private Car Use", *European Economic Review*, Vol. 34 No. 5, July 1990, 971-985.

[8] Eyster, Erik, *Rationalizing the Past: A Taste for Consistency*, Nuffield College, Oxford, 15 November 2002.

[9] Friedman, Daniel, Kai Pommerenke, Rajan Lukose, Garrett Milam, and Bernardo A. Huberman, "Searching for the sunk cost fallacy", *Experimental Economics*, Vol. 10, No. 1, March 2007, 79-104.

[10] Gourville, J. T. and Soman, D. "Payment Depreciation: The Behavioral Effects of Temporally Separating Payments from Consumption", *Journal of Consumer Research*, Vol. 25, September 1998, 160-174.

[11] Hastings, Justine, and Jesse M. Shapiro, "Fungibility and Consumer Choice: Evidence from Commodity Price Shocks", *Quarterly Journal of Economics*, 2013, doi: 10.1093/qje/qjt018.

[12] Just, David R., and Brian Wansink, "The Flat-Rate Pricing Paradox: Conflicting Effects of "All-You-Can-Eat" Buffet Pricing", *The Review of Economics and Statistics*, Vol. 93, No. 1, 2011, 193-200.

[13] Kanodia, Chandra, Robert Bushman, and John Dickhaut, "Escalation Errors and the Sunk Cost Effect: An Explanation Based on Reputation and Information Asymmetries", *Journal of Accounting Research*, Vol. 27 No. 1, Spring 1989, 59-77.

[14] Lew, Yii Der, and Wai Yan Leong, "Managing Congestion in Singapore – A Behavioural Economics Perspective", *Journeys* (Land Transport Authority, Singapore), May 2009, 15-22.

[15] McAfee, R. Preston, Hugo M. Mialon, and Sue H. Mialon, "Do Sunk Costs Matter?" *Economic Inquiry*, Vol. 48, No. 2, 2010, 323-36.

[16] McCarthy, Anne M., Schoorman, F. David and Cooper, Arnold C. "Reinvestment decisions by entrepreneurs: Rational decision-making or escalation of commitment?" *Journal of Business Venturing*, Vol. 8, 1993, 9-24.

[17] Phillips, Owen R., Raymond C. Battalio, and Carl A. Kogut, "Sunk and Opportunity Costs in Valuation and Bidding", *Southern Economic Journal*, Vol. 58, No. 1, 1991, 112-28.

[18] Png, Ivan, *Managerial Economics*, 4th edition, Abingdon, UK: Routledge, 2012.

[19] Staw, Barry M., "Knee-Deep in the Big Muddy: A Study of Escalating Commitment to a Chosen Course of Action", *Organizational Behavior and Human Performance*, Vol. 16, No. 1, June 1976, 27-44.

[20] Staw, Barry M., and Ha Hoang, "Sunk costs in the NBA: Why draft order affects playing time and survival in professional basketball", *Administrative Science Quarterly*, Vol. 40, No. 3, 1995, 474-494.

[21] Staw, Barry M., Sigal G. Barsade, and Kenneth W. Koput, "Escalation at the credit window: A longitudinal study of bank executives' recognition and write-off of problem loans", *Journal of Applied Psychology*, Vol. 82, No. 1, 1997, 130-142.

[22] Thaler, Richard, "Towards a Positive Theory of Consumer Choice", *Journal of Economic Behavior and Organization*, Vol. 1 No. 1, March 1980, 39-60.

[23] Thaler, Richard, "Saving, fungibility and mental accounts", *Journal of Economic Perspectives*, Vol. 4, 1990, 193-205.

[24] Thaler, Richard, "Mental Accounting Matters", *Journal of Behavioral Decision Making*, Vol. 12 No. 3, September 1999, 183-206.

Appendix

Generalizing (15), the driver's utility in month t (strictly, age of the car) is $U(q_t, t, c_t, g_t, R, S)$, where q_t, c_t, g_t are usage, unit congestion cost, and unit gasoline cost respectively, R is the retail price of the car and S is the sunk cost. Using the first-order condition, we can characterize the optimal usage, $q_t^*(t, c_t, g_t, R, S)$.

Consider how the optimal usage varies with the retail price,

$$\frac{dq_t^*}{dR} = \frac{\partial q_t^*}{\partial R}(t, c_t, g_t, R, S) + \frac{\partial q_t^*}{\partial S}(t, c_t, g_t, R, S) \cdot \frac{dS}{dR}. \tag{28}$$

In (28), the partial derivative of usage with respect to the retail price, $\partial q_t^*/\partial R$, represents the selection effect, that buyers who drive more are willing to pay a higher price. The partial derivative of usage with respect to the sunk cost, $\partial q_t^*/\partial S$, represents the sunk cost effect.

The variation of usage with respect to the retail price, (28), does not distinguish the effects of selection and sunk costs. To distinguish the two effects, we study the variation of usage with respect to retail price and *age of the car*. Differentiating (28) with respect to t,

$$\frac{d^2 q_t^*}{dRdt} = \frac{\partial^2 q_t^*}{\partial R \partial t}(t, c_t, g_t, R, S) + \frac{\partial^2 q_t^*}{\partial S \partial t}(t, c_t, g_t, R, S) \cdot \frac{dS}{dR} + \frac{\partial q_t^*}{\partial S}(t, c_t, g_t, R, S) \cdot \frac{d^2 S}{dRdt}. \tag{29}$$

Our identifying assumption is that the propensity of drivers who pay higher retail prices to drive more does not vary with car age, $\partial^2 q_t^*/\partial R \partial t = 0$. In addition, the retail price and sunk cost do not vary with the age of the car, $d^2 S/dRdt = 0$. Hence, (29) simplifies to

$$\frac{d^2 q_t^*}{dRdt} = \frac{\partial^2 q_t^*}{\partial S \partial t}(t, c_t, g_t, R, S) \cdot \frac{dS}{dR}. \tag{30}$$

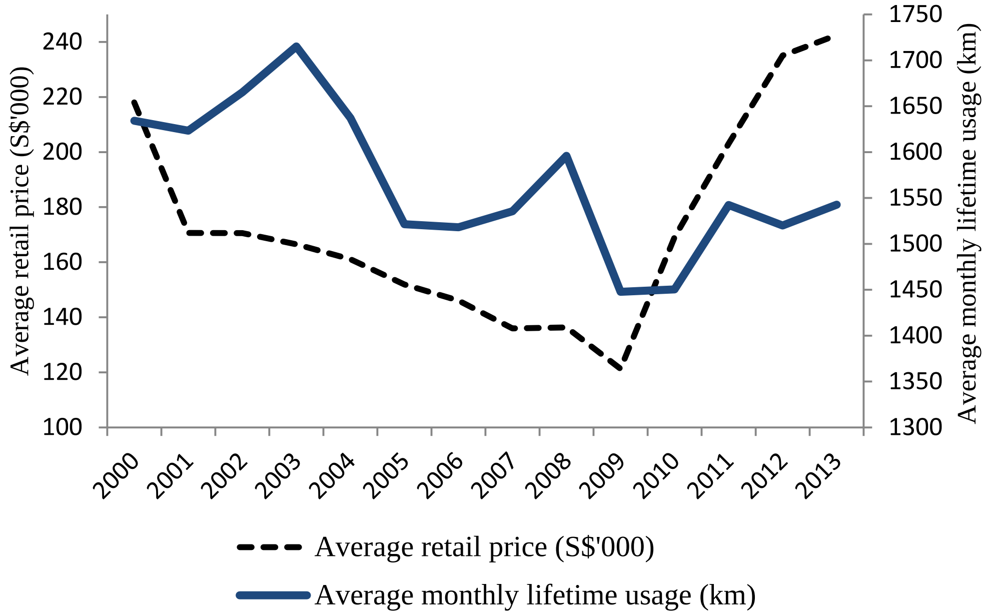
It follows from (30),

$$\frac{d^2 q_t^*}{dRdt} \text{ is proportional to } \frac{\partial^2 q_t^*}{\partial S \partial t}(t, c_t, g_t, R, S). \tag{31}$$

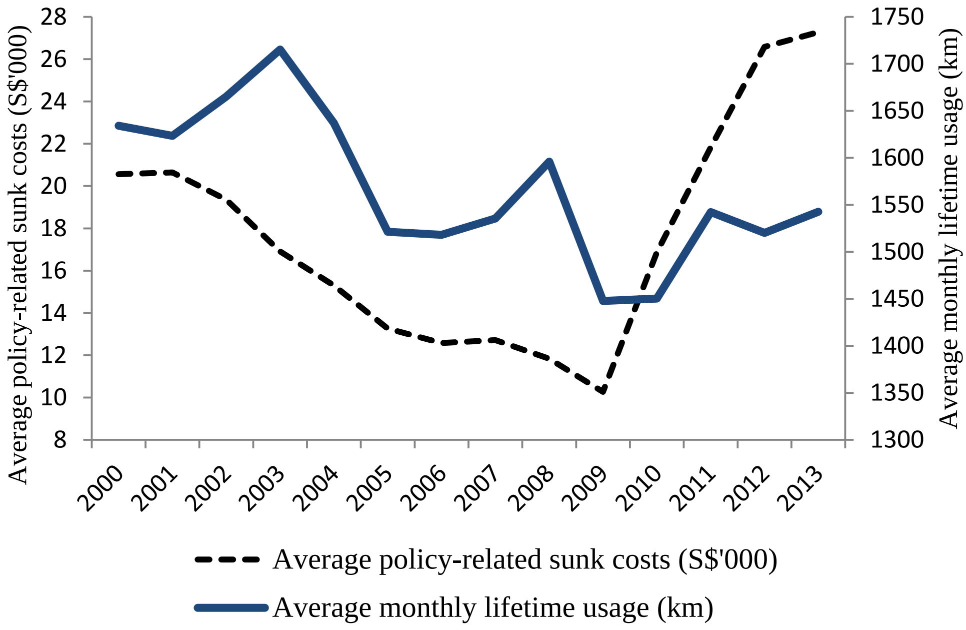
This suggests, that varying the rate of change in usage over time with retail price one can trace the sunk-cost effect on usage over time.

Figure 1. Monthly lifetime usage, retail car price, and policy-related sunk cost

(A)

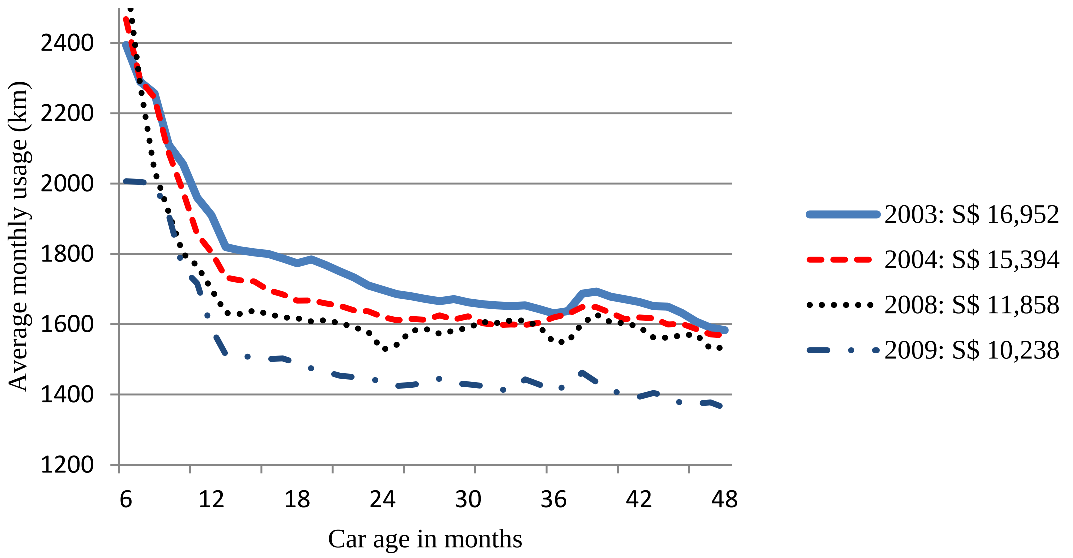


(B)



Notes: For the most popular model in the sample (3,403 cars). Panel A depicts the average retail price of cars (in S$'000) on the left-hand axis, and average monthly usage over life of the car (in kilometers) on the right-hand axis. Panel B depicts the average policy-related sunk costs (in S$'000) on the left-hand axis, and average monthly usage over life of car (in kilometers) on the right-hand axis.

Figure 2. Average monthly usage and policy-related sunk cost



Note: For the most popular model in the sample (3,403 cars). Legend presents year and average policy-related sunk costs (S$) of cars bought in that year. Monthly average usage is interpolated for the months between successive services.

Figure 3. COE and ARF rebate structure

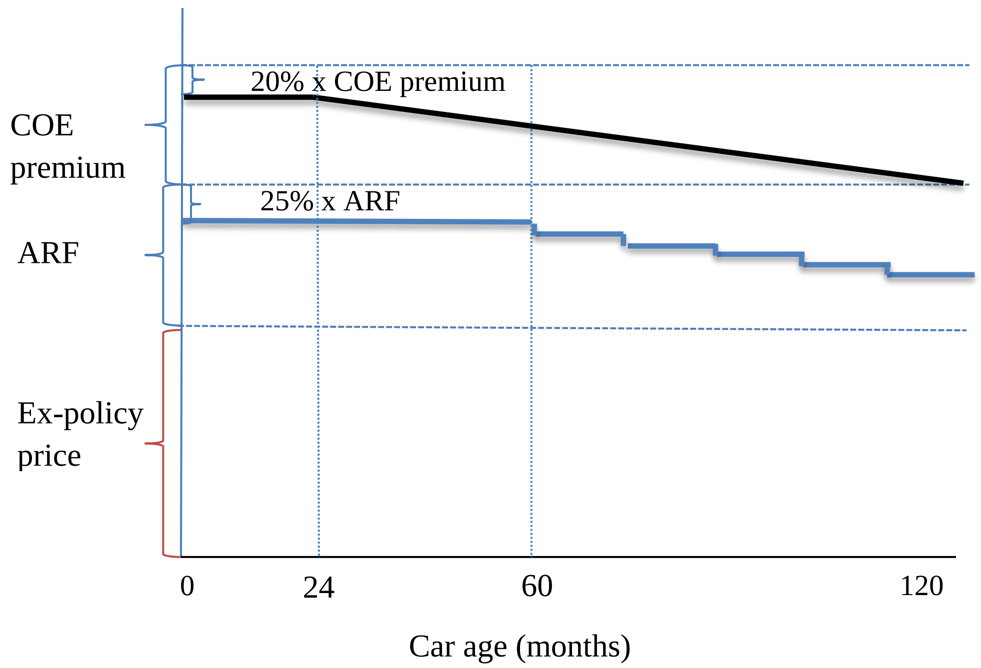
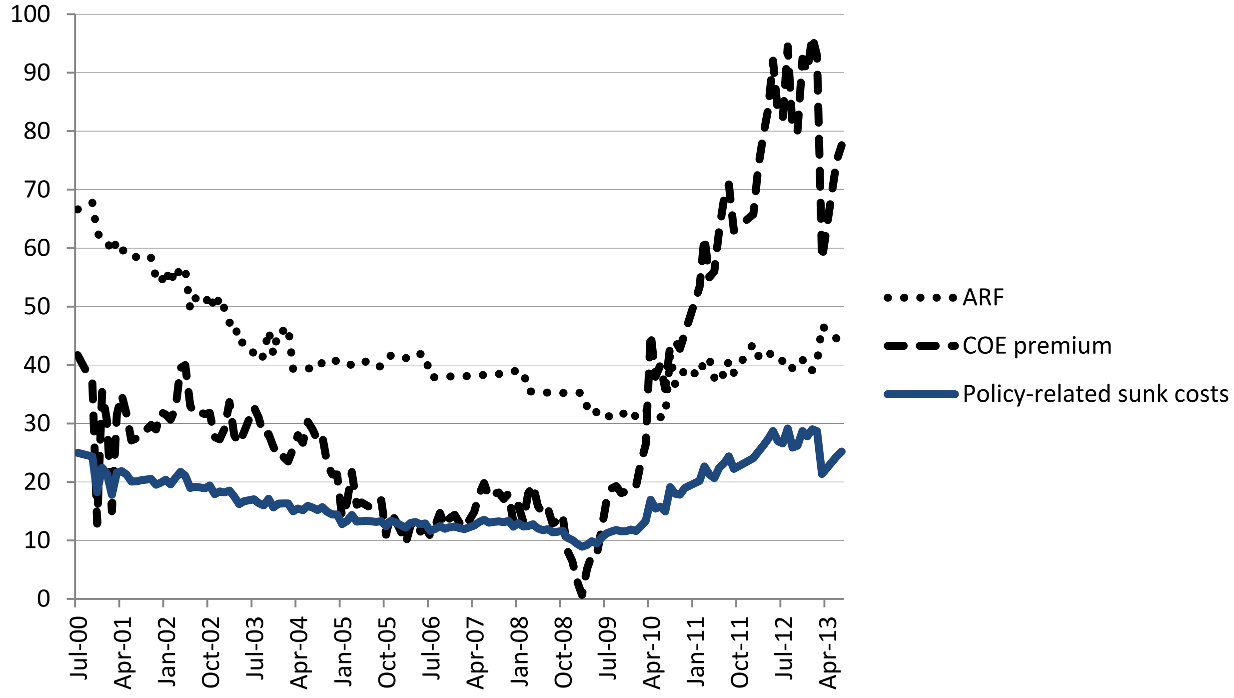
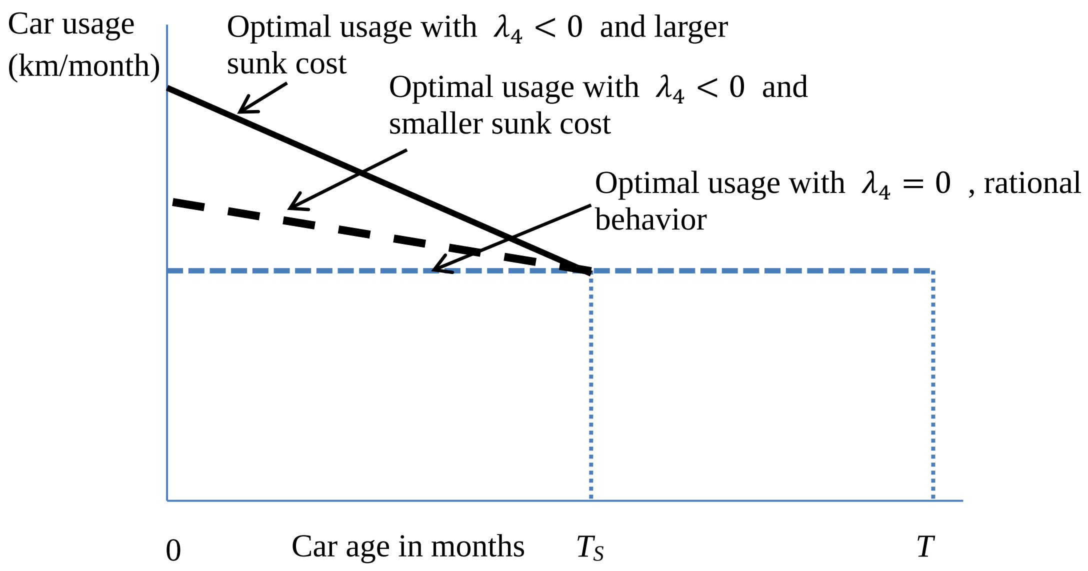


Figure 4. COE premium, ARF and policy-related sunk costs



Notes: For the most popular model in the sample (3,403 cars). COE premium, ARF and policy-related sunk costs in S$'000.

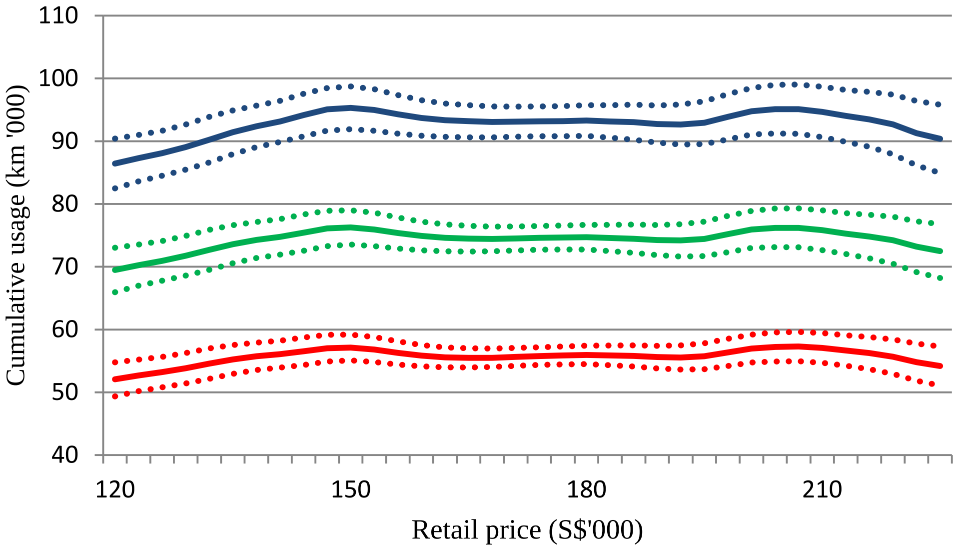
Figure 5. Effect of mental accounting for sunk cost



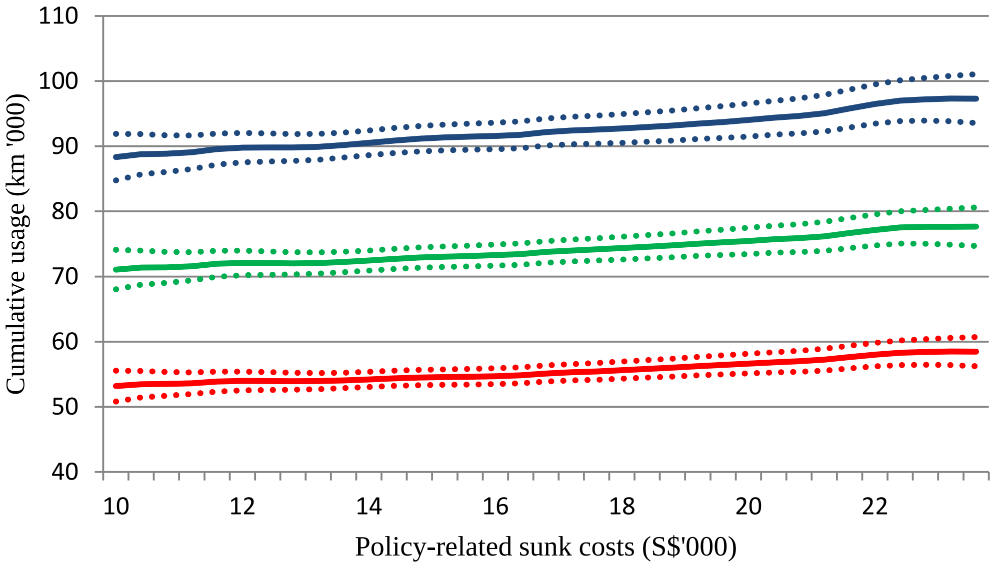
Notes: Monthly car usage assuming cost of gasoline and congestion fixed over time, and no time (age)-dependent marginal benefit.

Figure 6. Cumulative usage, retail car price, and policy-related sunk costs

(A)

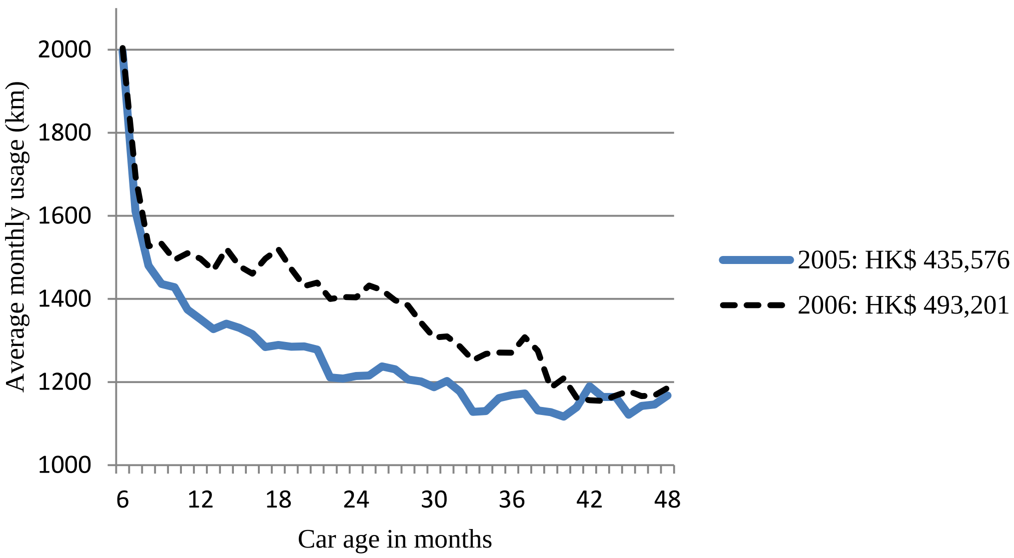


(B)



Notes: For the entire sample (8,264 cars). Regression graphs and standard errors generated using a locally weighted polynomial regression. The dashed curves represent the upper and lower bounds of the 95% confidence interval. Panel A depicts regressions of cumulative usage up to 3 years (lower graph), 4 years (middle graph), and 5 years (upper graph) on retail price (in S$'000). Panel B depicts regressions of cumulative usage up to 3 years (lower graph), 4 years (middle graph), and 5 years (upper graph) on the policy-related sunk costs (in S$'000).

Figure 7. Average monthly usage and retail price (Hong Kong)



Note: For the most popular model in the sample (591 cars). Legend presents average monthly usage and retail price of car. Monthly average usage is interpolated for the months between successive services.

Table 1. COE premium

VARIABLE	(a) COE premium	(b) Change in COE premium
Constant	163.856*	0.369
	(87.964)	(0.470)
COE quota ('000)	-4.667***	
	(1.020)	
Change in COE quota		-2.088*
		(1.249)
CPI fuel index	-0.026	
	(0.115)	
Change in CPI fuel index		-0.002
		(0.144)
Cars per km	-1.780*	
	(0.991)	
Change in cars per km		-1.415
		(1.246)
Quarterly GDP	0.800*	
	(0.432)	
Change in quarterly GDP		0.530
		(0.409)
Year fixed effects	Yes	No
Quarter fixed effects	Yes	No
Observations	131	130
R-squared	0.953	0.04

Notes: Sample: April 2002 – December 2013 (data on COE quota available since April 2002), COE premia in S$'000; GDP in S$ billion. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2. Summary statistics

VARIABLE	Unit	Mean	Standard deviation	Min	Max
Usage	'000 kilometers per month	1.545	0.529	0.539	4.189
Age of car at last service	Months	49.2	21.9	5	119
Retail price	S$000'000	0.177	0.031	0.110	0.317
ARF	S$000'000	0.047	0.009	0.031	0.092
COE premium	S$000'000	0.027	0.016	0.001	0.096
Policy-related sunk cost	S$000'000	0.017	0.004	0.009	0.032
Gasoline price	2006 January = 100	106.64	16.80	69.10	130.82
Congestion	Cars per kilometer	99.27	7.47	82.85	106.33

Note: US$1 = S$1.54 (January 1, 2007).

Table 3. Sunk cost and car usage: Reduced form estimates

	(1)	(2)	(3)
Price x car age	-0.057***		
	(0.012)		
Ex-policy price x car age		-0.019	-0.014
		(0.034)	(0.029)
COE sunk cost x car age		-0.598**	
		(0.276)	
ARF sunk cost x car age		-0.426	
		(0.315)	
Policy-related sunk cost			-0.518***
			(0.171)
Control	Yes	Yes	Yes
Observations	36,931	36,931	36,931
Cars	8,264	8,264	8,264
F-statistics	21.7	7.5	11.2
p-value	<0.001	<0.001	<0.001

Notes: Estimated by OLS; Dependent variable is change in average usage (‘000 km per month) between successive services; Control variables (not reported): difference in average fuel price, difference in average cars per km, difference in average age, difference in average age squared, level of price and sunk cost components, large cars (>2000cc), and year of registration dummy variables. F-statistics calculated versus a model without price or sunk cost components. Robust standard errors clustered by car in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 4. Sunk cost and car usage: Structural estimates

VARIABLE	(a) Rational model	(b) Horizon: 24 mths	(c) Horizon: 36 mths	(d) Horizon: 48 mths	(e) Horizon: 60 mths	(f) Horizon: 72 mths
Gasoline price, β_1x10	0.007**	0.007**	0.007**	0.006**	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Congestion, β_2	0.006***	0.007***	0.009***	0.004***	0.004***	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Age, ϕ_1x10	0.084***	0.055***	0.192***	0.290***	0.252***	0.247***
	(0.004)	(0.010)	(0.014)	(0.014)	(0.013)	(0.014)
Age squared, ϕ_2x100	-0.009***	-0.006***	-0.017***	-0.022***	-0.016***	-0.013***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Policy-related sunk cost, λ_{41}		-0.315***	-0.280***	-0.185***	-0.154***	-0.136***
		(0.085)	(0.067)	(0.058)	(0.054)	(0.052)
Ex-policy price, λ_{42}		-0.013	-0.014	-0.017	0.007	0.008
		(0.014)	(0.011)	(0.011)	(0.011)	(0.009)
Remaining horizon, λ_2x10		0.098***	-0.017	-0.109***	-0.118***	-0.128***
		(0.033)	(0.029)	(0.030)	(0.032)	(0.030)
Observations	36,931	36,931	36,931	36,931	36,931	36,931
Cars	8,264	8,264	8,264	8,264	8,264	8,264
R-squared	0.006	0.007	0.008	0.011	0.009	0.008
Ln likelihood	-23,928	-23,916	-23,895	-23,840	-23,874	-23,886
F-test statistic (vs rational model)	NA	8.616	22.534	58.969	36.151	28.162
p-value	NA	<0.001	<0.001	<0.001	<0.001	<0.001
Elasticity	NA	0.044***	0.057***	0.050***	0.052***	0.060***
Elasticity s.e.	NA	(0.012)	(0.014)	(0.016)	(0.018)	(0.023)

Notes: Estimated by OLS. Dependent variable is first difference of usage (‘000 km per month); Gasoline price is represented by CPI-fuel and congestion is represented by the number of cars per km; Age is in number of months since registration; Sunk cost, ex-policy price and car price are in S$000‘000. Robust standard errors clustered by car in parentheses (*** p<0.01, ** p<0.05, * p<0.1). F-test evaluates null hypothesis that coefficients of policy-related sunk cost, ex-policy price, and remaining horizon jointly equal to zero, i.e., rational model is valid.

Table 5. Heterogeneous effects and robustness checks

VARIABLE	(a) Preferred model	(b) Small/large cars	(c) Small cars	(d) Large cars	(e) Separate COE/ARF sunk costs	(f) Salience	(g) Retail price sunk cost
Gasoline price, β_1x10	0.006**	0.006**	0.009**	0.003	0.008***	0.006**	0.006**
	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Congestion, β_2	0.004***	0.004***	0.006***	0.003	0.008***	0.003*	0.004***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Age, ϕ_1x10	0.290***	0.289***	0.312***	0.268***	0.251***	0.284***	0.289***
	(0.014)	(0.014)	(0.021)	(0.020)	(0.037)	(0.015)	(0.014)
Age squared, ϕ_2x100	-0.022***	-0.022***	-0.023***	-0.020***	-0.015***	-0.021***	-0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Policy-related sunk cost, λ_{41}	-0.185***					-0.283***	
	(0.058)					(0.067)	
Policy-related sunk cost (small cars), λ_{41}^{s}		-0.187**	-0.171**				
		(0.075)	(0.081)				
Policy-related sunk cost (large cars), λ_{41}^{l}		-0.155*		-0.169*			
		(0.082)		(0.087)			
COE-related sunk cost, λ_{41}^{c}					-0.694***		
					(0.070)		
ARF-related sunk cost, λ_{41}^{a}					-0.091		
					(0.092)		
Ex-policy price, λ_{42}	-0.017				0.014	-0.012	
	(0.011)				(0.011)	(0.011)	
Ex-policy price (small cars), λ_{42}^{s}		-0.023	0.003				
		(0.015)	(0.018)				
Ex-policy price (large cars), λ_{42}^{l}		-0.023		-0.037**			
		(0.015)		(0.018)			
Retail price, $\lambda_4\rho$							-0.026***
							(0.007)

COE premium paid less current COE premium, $\lambda_{41}^{\text{sal}}$						0.055***	
						(0.015)	
Remaining horizon, λ_2x10	-0.109***	-0.104***	-0.145***	-0.073***		-0.009***	-0.112***
	(0.017)	(0.018)	(0.023)	(0.026)		(0.002)	(0.017)
Remaining horizon COE, λ_{21}x10					0.014***		
					(0.002)		
Remaining horizon ARF, λ_{22}x10					-0.015***		
					(0.003)		
Observations	36,931	36,931	17,162	19,769	36,931	36,931	36,931
Cars	8,264	8,264	4,137	4,127	8,264	8,264	8,264
R-squared	0.011	0.011	0.013	0.009	0.011	0.011	0.011
Ln likelihood	-23,840	-23,840	-10,797	-13,032	-23,837	-23,837	-23,841
F-test statistic (vs rational model)	58.969	44.349	44.253	45.654	50.292	60.982	175.866
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Elasticity	0.050***	0.046**	0.045**	0.047*	0.059***	0.077***	0.073***
Elasticity s.e.	(0.016)	(0.021)	(0.022)	(0.024)	(0.006)	(0.018)	(0.020)

Notes: Estimated by OLS. Dependent variable is first difference of usage (‘000 km per month); Gasoline price is represented by CPI-fuel and congestion is represented by the number of cars per km; Age is in number of months since registration; Sunk cost, ex-policy price and car price are in S$000‘000. Robust standard errors clustered by car in parentheses (*** p<0.01, ** p<0.05, * p<0.10). F-test evaluates null hypothesis that coefficients of policy-related sunk cost, ex-policy price, and remaining horizon jointly equal to zero, i.e., rational model is valid.

Table 6. Likelihood of selling car

VARIABLES	(a) Retail price	(b) Price components	(c) Sunk cost
Price	0.252		
	(1.159)		
Ex-policy price		-2.920	-1.917
		(2.266)	(1.730)
Policy-related sunk cost			19.404
			(12.007)
COE premium		1.946	
		(3.128)	
ARF		8.288	
		(5.763)	
Observations	8,264	8,264	8,264
Ln likelihood	-49,514	-49,513	-49,513
Chi-squared	4,801	4,833	4,790

Notes: Estimated by Cox proportional hazards regression; length of ownership stipulated to be car age at last service; and the observation considered to be censored if the last service was between July 2013 and June 2014. Each cell reports the estimated coefficient and the sign of the coefficient indicates the direction of effect on the hazard ratio. Control variables include: mileage and mileage squared, engine and year of registration fixed effects. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 7. Service visits

	(a) Retail price	(b) Price components	(c) Sunk cost
Price	0.210		
	(0.222)		
Ex-policy price		0.530	0.662**
		(0.347)	(0.275)
Policy-related sunk cost			-2.698
			(1.892)
COE premium		-0.648	
		(0.428)	
ARF		-0.154	
		(1.060)	
Observations	8,264	8,264	8,264
Pseudo R-squared	0.2055	0.2055	0.2055
Ln likelihood	-15,031	-15,031	-15,031
Chi-squared	44,562	44,822	44,743

Notes: Estimated by Poisson regression; Dependent variable is number of service visits; Retail price, ex-policy price, and policy-related sunk cost in S$000‘000; Control variables: Mileage (in ‘000 km) and mileage squared; car age (in months) and car age squared; engine size and year of registration fixed effects. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 8. Hong Kong: Summary statistics

VARIABLES		Mean	Std dev	Min	Max
Usage	'000 kilometers/mth	1.106	0.535	0.244	4.347
Age of car at last service	Months	50.8	22.4	8	119
Retail price	HK$000'000	0.514	0.121	0.241	0.794
Gasoline price	2006 January = 100	97.9	15.22	73.6	123.9
Congestion	Cars per kilometer	101.4	5.33	95.4	116.2

Notes: US$1 = HK$7.8 (January 1, 2007).

Table 9. Hong Kong: Sunk cost and car usage

VARIABLES	(a) Rational model	(b) Horizon: 20 mths	(c) Horizon: 24 mths	(d) Horizon: 28 mths	(e) Horizon: 32 mths	(f) Horizon: 36 mths
Gasoline price,	-0.004	-0.001	-0.000	-0.001	-0.001	-0.002
β_1x10	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Congestion, β_2	0.014**	0.009	0.008	0.007	0.007	0.009
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Age, ϕ_1x10	-0.037***	-0.143***	-0.141***	-0.127***	-0.048	0.066
	(0.014)	(0.031)	(0.037)	(0.044)	(0.049)	(0.052)
Age squared,	-0.001	0.008***	0.007**	0.005	-0.002	-0.010**
ϕ_2x100	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Retail price, $\lambda_4\rho$		-0.023***	-0.022***	-0.021***	-0.016***	-0.012**
		(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
Remaining		0.239***	0.212***	0.186***	0.090	-0.022
horizon, λ_2x10		(0.052)	(0.051)	(0.055)	(0.055)	(0.050)
Observations	3,765	3,765	3,765	3,765	3,765	3,765
Cars	962	962	962	962	962	962
R-squared	0.023	0.027	0.026	0.026	0.025	0.025
Ln likelihood	-2,572	-2,564	-2,565	-2,566	-2,569	-2,568
F-test statistic		54.086	45.622	39.659	25.027	29.179
p-value		<0.001	<0.001	<0.001	<0.001	<0.001
Elasticity		0.099***	0.113***	0.125***	0.110***	0.093***
Elasticity s.e.		(0.026)	(0.026)	(0.036)	(0.041)	(0.039)

Notes: Estimated by OLS. Dependent variable is first difference of usage ('000 km per month); Gasoline price is representted by CPI-fuel and congestion is represented by the number of cars per km; Age is in number of months since registration; retail price are in HK$000'000. Robust standard errors clustered by car in parentheses (*** p<0.01, ** p<0.05, * p<0.1). F-test evaluates null hypothesis that coefficients of policy-related sunk cost, ex-policy price, and remaining horizon jointly equal to zero, i.e., rational model is valid.

Table S1. Robustness checks

VARIABLE	(a) Preferred estimate	(b) Cars older than 3 years	(c) Including outliers	(d) Maximum mthly usage 3,000km
Gasoline price, β_1x10	0.006**	0.005	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Congestion, β_2	0.004***	0.005***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Age, ϕ_1x10	0.290***	0.288***	0.295***	0.283***
	(0.014)	(0.017)	(0.015)	(0.014)
Age squared, ϕ_2x100	-0.022***	-0.021***	-0.022***	-0.021***
	(0.001)	(0.001)	(0.001)	(0.001)
Policy-related sunk cost, λ_{41}	-0.185***	-0.284***	-0.118**	-0.185***
	(0.058)	(0.074)	(0.060)	(0.058)
Ex-policy price, λ_{42}	-0.017	-0.015	-0.024**	-0.017*
	(0.011)	(0.013)	(0.010)	(0.010)
Remaining horizon, λ_2x10	-0.109***	-0.009***	-0.011***	-0.010***
	(0.030)	(0.002)	(0.002)	(0.002)
Observations	36,931	27,931	37,219	36,416
Cars	8,264	6,242	8,401	8,176
R-squared	0.011	0.011	0.011	0.010
Ln likelihood	-23,840	-18,675	-24,493	-23,164
F-test statistic (vs rational model)	58.969	59.411	55.341	58.257
p-value	<0.001	<0.001	<0.001	<0.001
Elasticity	0.050***	0.072***	0.030***	0.072***
Elasticity s.e.	(0.016)	(0.019)	(0.015)	(0.019)

Notes: Estimated by OLS; Dependent variable is first difference of usage (‘000 km per month); Gasoline price is represented by CPI-fuel and congestion is represented by the number of cars per km; Age is in number of months since registration; Sunk cost, ex-policy price and car price are in S$000‘000. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table S2. Sunk cost and car usage: Structural estimates (with CPI adjusted price, sunk costs)

VARIABLE	(a) Rational model	(b) Horizon: 24 mths	(c) Horizon: 36 mths	(d) Horizon: 48 mths	(e) Horizon: 60 mths	(f) Horizon: 72 mths
Gasoline price,	0.007**	0.008**	0.007**	0.006**	0.008***	0.008***
β_1x10	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Congestion cost, β_2	0.006***	0.007***	0.009***	0.004***	0.003**	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age, ϕ_1x10	0.084***	0.053***	0.187***	0.285***	0.250***	0.245***
	(0.004)	(0.010)	(0.015)	(0.014)	(0.013)	(0.014)
Age squared,	-0.009***	-0.006***	-0.016***	-0.021***	-0.016***	-0.013***
ϕ_2x100	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Policy-related sunk		-0.424***	-0.344***	-0.226***	-0.182***	-0.165***
cost, λ_{41}		(0.093)	(0.071)	(0.062)	(0.058)	(0.056)
Ex-policy price, λ_{42}		-0.013	-0.015	-0.018*	0.006	0.007
		(0.014)	(0.011)	(0.011)	(0.011)	(0.009)
Remaining horizon,		0.116***	-0.002	-0.099***	-0.111***	-0.122***
λ_2x10		(0.016)	(0.017)	(0.018)	(0.019)	(0.017)
Observations	36,931	36,931	36,931	36,931	36,931	36,931
Cars	8,264	8,264	8,264	8,264	8,264	8,264
R-squared	0.006	0.007	0.008	0.011	0.009	0.008
Ln likelihood	-23928	-23912	-23892	-23839	-23874	-23886

Notes: Estimated by OLS. Dependent variable is first difference of usage (‘000 km per month); Gasoline price is represented by CPI-fuel and congestion is represented by the number of cars per km; Age is in number of months since registration; Sunk cost, ex-policy price and car price are in S$000‘000, and deflated by CPI/100 (Jan 2000=100). Robust standard errors clustered by car in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Figure S1. Length of ownership