Sunk Cost Fallacy in Driving the World’s Costliest Cars

Teck-Hua Ho*, I.P.L. Png†, and Sadat Reza‡

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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. It predicts that usage increases in the sunk cost, and attenuates with time at a rate that increases in the sunk cost. The model nests conventionally rational behavior as a special case.

We take the model to a panel of 7,398 cars between 2001-2011 in Singapore. During that period, the sunk cost involved in a new car purchase varied substantially with continuing government policy. We find robust evidence of a sunk cost fallacy. The elasticity of usage with respect to the sunk cost is 0.164 (s.d. 0.008). An increase in the sunk cost by S$4,500 (the outcome of government policy between 2009 and 2010) would be associated with an increase in monthly usage by 70.9 kilometers or 4.5% in the first four years of ownership. Our results are robust to various checks including alternative controls for selection, differences in model and specification, and allowing for heterogeneous effects by car size.

Keywords: automobile, sunk costs, mental accounting, behavioral economics

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*University of California, Berkeley, and National University of Singapore; †National University of Singapore; ‡Nanyang Technological University. The authors contributed equally and are listed in alphabetical order: Ho: hoteck@haas.berkeley.edu; Png: ipng@nus.edu.sg; Reza: sreza@ntu.edu.sg. We thank Colin Camerer, Stefano Dellavigna, David Laibson, Ulrike Malmendier, Minjung Park, Matthew Rabin, Matthew Shum, Richard Thaler, and seminar participants at Caltech, Chinese University of Hong Kong, Conference on Evidence-based Public Policy Using Administrative Data in Singapore, Nanyang Technological University, Singapore Management University, Workshop on Behavioral Economics and Policy Design in Singapore, Singapore Economic Policy Forum, Summer Institute in Competitive Strategy at Berkeley, UC Berkeley, and the University of Michigan for comments and suggestions. We also thank Jia-An Tan, Danny Liew, Chong Lee Kee, Dinh Hoang Phuong Thao, and Chua Tziyuan for research assistance, and above all, an anonymous car dealer and the Land Transport Authority of Singapore for the data.
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. Since they are 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. Separately, Gourville and Soman (1998) observed “payment depreciation” among members of an athletic facility: monthly attendance peaked when the members paid their half-yearly installment, and then declined with time. In a recent field experiment at an all-you-can-eat-pizza restaurant, diners consumed less when the price was discounted (Just and Wansink 2011). These studies suggest that consumption is higher when consumers incur a higher sunk cost.

However, in two other field experiments, consumers did not evince the sunk cost fallacy. Ashraf et al. (2010) gave unannounced random discounts to Zambian consumers buying Clorin, a chemical to treat drinking water. Differences in the amount paid did not affect the consumers’ use of the chemical to treat water. Cohen and Dupas (2010) gave unannounced random discounts on insecticide-treated bed nets to patients in Kenyan prenatal clinics. There was no clear relation between the net price and usage of the nets.2

Thus far, studies of the sunk cost fallacy among consumers have yielded conflicting results. The different results might arise from differences in the saliency of the sunk cost in the various field settings. By contrast, in repeated situations such as driving car, the sunk costs would

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2In laboratory experiments, Phillips et al. (1991) and Friedman et al. (2007) also did not find evidence for sunk cost fallacy.
surely be more salient. Since the cost of (repeated) mistakes would be 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 costs, resulting in an even larger influence on behavior.

The effect of sunk costs on decision-making in repeated situations is particularly important as it has implications beyond consumer behavior, particularly for management of businesses and public administration. Here, we investigate whether consumers are influenced by sunk costs in repeated situations. Based on structural estimation of a model of mental accounting for sunk costs in the context of car usage in Singapore, we find robust evidence that sunk costs affect behavior. Specifically, the larger the sunk cost incurred in purchasing a car, the more that the owner drove and the more that driving attenuated with age of the car. Our results suggest that individuals do not self-correct (or do not fully self-correct) decision bias in repeated situations.

Car usage is an attractive setting for investigation of the effect of mental accounting on behavior in a repeated situation. 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) found that households engaged in mental accounting for expenditure on gasoline. The Singapore context is particularly attractive because government policies to restrict car ownership resulted in substantial variation in the price of new cars and the corresponding sunk costs incurred in new car purchase (and incidentally, caused Singapore cars to be the world’s most expensive). The government policies are long-standing and are well publicized, so the sunk costs are certainly salient to people in Singapore.

To investigate the effect of sunk costs on consumer behavior in a repeated situation, we first develop a behavioral model of utility maximization to understand how sunk costs might influence usage over time. The model assumes that car buyers mentally account for the

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3 Many studies have investigated the effect of sunk costs on decision-making 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; McCarthy et al. 1993; Staw et al. 1997; Barron et al. 2001). 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’ incentive problem through a two-stage estimation procedure, the effect of prior decisions remained significant but became much smaller.
sunk cost of a new car by amortizing the sunk cost relative to a target cumulative usage over a planning horizon (Gourville and Soman 1998; Thaler 1999). The model implies that car usage increases with the sunk cost and attenuates with age, and, importantly, that the rate of attenuation with age increases in the sunk cost. The behavioral model of mental accounting nests conventionally rational behavior, where sunk costs do not affect decision making, as a special case.

Second, we take the model to an unbalanced panel of 7,398 units of one brand of cars in Singapore between 2001-2011. For each car, we have the accumulated driving distance (in kilometers) at each service. During the period of study, the application of continuing government policies resulted in substantial variation in the sunk costs associated with buying a new car. We exploit this variation in structural estimation of the model of mental accounting.

Figure 1 depicts the monthly usage by vintage of car over the period of study for the most popular model in our sample, and the corresponding average retail price and the sunk portion of policy-related charges (we explain the structure of the policy-related charges and sunk costs in Section 2 below). During the period of study, the policy-related charges declined, and in tandem, the retail price of cars decreased over time. As Figure 1 shows, monthly lifetime usage was correlated with the retail price and policy-related sunk costs. The monthly usage of earlier vintages – cars bought in earlier years – tended to be higher than that of later vintages.4

However, the correlation in Figure 1 between car usage and policy-related sunk costs can also be explained by selection, specifically, that, when the prices of car are high, the people who buy cars tend to be those who want to drive more. As a result, higher policy-related charges that cause higher car prices would be associated with more car usage. 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 over time increases with the sunk cost. By contrast, selection does not imply any relation between car prices and the rate

4As of December 17, 2013, the exchange rate was US$1 = S$1.26. To an American economist, car prices exceeding $170,000 might seem outlandish. We stress that, in Europe and the United States, the brand of cars in our sample would be considered “middle class”.

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of attenuation.

Figure 2 depicts monthly usage with age of the car for four vintages (2003-06) of the most popular model in our sample over the first 48 months.\footnote{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 recommended at cumulative usage of 15,000 kilometers. So, with average usage of 1,569 kilometers a month, the first service of the car would be in the ninth month. We observe that, 194 cars (2.6 % of the total) were presented for first service before they were 6 months old. If owners of these cars had followed 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, and hence, they exhibited lower usage. Accordingly, we focus on usage after the sixth month of ownership.} As depicted in Figure 1, the retail price and policy-related sunk costs fell steadily from 2003 until 2006. The lower the policy-related sunk costs and retail price were, the lower the monthly usage tended to be, for all vintages of the car. More importantly, consistent with the central implication of the behavioral model, the lower the policy-related sunk costs were, the slower was the rate at which usage attenuated with age of the car.

Besides focusing on the attenuation of usage with car age, our empirical strategy addresses the alternative explanation of selection in two other ways. One is to estimate the model 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 and car age, such as that arising from selection. All of our estimates are cast in terms of first differences. The other way of addressing selection is to explicitly model the marginal benefit from usage as varying according to the retail price of the car. Our results are robust to this alternative specification.

Our structural estimates suggest that the elasticity of usage with respect to the sunk cost of a car was 0.164(s.d. 0.008). An increase in the sunk cost by S$4,500 (the outcome of continuing government policy between 2009 and 2010) would have been associated with an increase in monthly usage by 70.9 kilometers or 4.5% in the first four years of usage. This effect is robust to various checks including alternative controls for selection, differences in model and specification, and allowing for heterogeneous effects by car size.

In the remainder of this paper, Section 2 describes Singapore government policies towards car ownership and usage. Section 3 presents a behavioral model of mental accounting for sunk costs.
costs, Section 4 presents the empirical strategy, and Section 5 introduces the data. Section 6 reports structural estimates of the behavioral model, Section 7 shows that our interpretation is robust to alternative explanations of the results in terms of selection, 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 actively addressed traffic congestion in two ways—pricing road usage and limiting the vehicle population. While the government’s policies to limit the number of vehicles targets all vehicles—cars, buses, trucks, and motorcycles, 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.\(^6\)

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:

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

\(^6\)No cars are manufactured in Singapore. Since all are imported, the import price equals the wholesale cost.
where $\pi_{ARF}$ and $\pi_{tax}$ 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. In the year 2011, the average price of cars in our sample (what in Europe and the United States would be considered a typically “middle class” brand) was S$223,000 (US$178,000).

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 was capped at 80% of the COE premium, and so, 20% of the COE premium was sunk upon purchase of the car. Thereafter, the rebate was pro-rated linearly by the days remaining until the car reached 10 years of age. The COE expires after 10 years, so, the owner either had to buy a new 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 was capped at 75% of the ARF, and so, 25% of the ARF was sunk upon purchase of the car. Thereafter, the rebate was pro-rated, step-wise, by the number of years remaining until the car reached 10 years of age. Figure 3 depicts the structure of COE and ARF rebates and the corresponding sunk costs.

Consequently, in Singapore, the purchase of a new car involves two policy-related sunk costs:7

- 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 would forego the pro-rated part of the COE premium each day, a cost that would vary with age but not usage.

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7In the behavioral model, we also allow for a sunk cost on the car itself, unrelated to government policy.
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 would forego the pro-rated part of the ARF each year, a cost that would vary with the year but not within the year and not with usage.

Hence, sunk costs may influence driver behavior up to the first 60 months of car ownership. Thereafter, we expect sunk costs to have no effect.

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 would vary, and so, the COE-related sunk cost of a new car purchase would vary.

The ARF and the 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 would 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 2001 to 2009. 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$3,400, compared with the mean sunk costs of S$16,363. We exploit this variation to identify the effect of sunk costs on car usage.

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, price of fuel, congestion (as measured by number of cars per kilometer of road), and macroeconomic factors (quarterly GDP and year fixed effects). 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 and change in number of cars per kilometer are significant. These results suggest that changes in COE premia are primarily the result of exogenous factors beyond the control of individual drivers.

– 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 behavioral model of driving behavior. We begin with a conventionally rational model, and then extend the model to include mental accounting for sunk cost. The behavioral model nests the conventionally rational model as a special case, and as a consequence, we can empirically test whether the data reject the rational model.

3.1 Conventionally 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

$$U(q_t, t) = B(q_t, t) - C(q_t, t) - D(t), \hspace{1cm} (2)$$

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. Note that depreciation is independent of $q_t$.

Let the benefit from usage,

$$B(q_t) = \theta_0 + \theta_1 q_t - \theta_2 q_t^2 + \phi(t) q_t, \hspace{1cm} (3)$$

or equivalently the marginal benefit from usage,

$$B'(q_t) = \theta_1 - 2\theta_2 q_t + \phi(t). \hspace{1cm} (4)$$
We assume that $\theta_1, \theta_2, \phi(\cdot) > 0$, and are such that the marginal benefit, $B'(\cdot) > 0$, and the marginal benefit diminishes with usage, $B''(\cdot) < 0$.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 $\phi_1$ and $\phi_2$.

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

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

where $\beta_1, \beta_2 > 0$, and $\beta_1 g_t$ is the cost of the gasoline per kilometer of usage and $\beta_2 c_t$ is the cost of congestion per kilometer of usage.

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

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

represent the “ex-policy price” of the car. Based on the rebate structure of the COE and ARF (described in Section 2 above), we model the depreciation of the retail price as:

$$D(t) = \delta_0[P - s_0] + \delta_1(t)[\text{ARF} - s_1] \cdot 1(t > 60) + \delta_2(t)[\text{COE} - s_2] \cdot 1(t > 24) \tag{8}$$

where $s_0$, $s_1$, and $s_2$ represent the sunk portions of the ex-policy price, ARF, and COE premium, and $\delta_0$ is the depreciation rate of the ex-policy price, and $\delta_1(t)$ and $\delta_2(t)$ are the

8The quadratic functional form, (3), may be interpreted as a Taylor series approximation of a more general benefit function that exhibits diminishing marginal benefit.
depreciation functions of the ARF and COE premium (as given in Figure 3).

Substituting above, the consumer’s utility is

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

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

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

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

*Proof.* In each month \( t \), the consumer chooses \( q_t \) to maximize

\[ \sum_{\tau=t}^{T} U_t = \sum_{\tau=t}^{T} \left[ \theta_0 + \theta_1 q_t - \theta_2 q_t^2 + [\phi_1 t + \phi_2 t^2] q_t - \beta_1 g_t q_t - \beta_2 c_t q_t - D(t) \right]. \] (11)

Maximizing (11) with respect to \( q_t \), the optimal usage is given by

\[ 2\theta_2 q_t^* = \theta_1 + \phi_1 t + \phi_2 t^2 - \beta_1 g_t - \beta_2 c_t, \] (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 is a function of both usage and mental accounting for the sunk cost. Specifically, the driver amortizes the sunk cost, \( S \), by the actual cumulative usage, \( Q_t \), relative to some target cumulative usage, \( \hat{Q} \), over a planning horizon, \( T_S \). Given the structure of the policy-related
sunk costs (as described in Section 2), we expect the sunk costs to be salient within the first 60 months of ownership (Gourville and Soman 1998; Thaler 1999). Accordingly, the planning horizon, $T_S$, would be 60 months, or perhaps less. 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 conventionally rational model.

Accordingly, we generalize the driver’s utility in month $t$ as

$$U(q_t, t) = \begin{cases} B(q_t) - C(q_t, t) - D(t) - \max \left\{ 0, \lambda S \cdot \left[ 1 - \frac{Q_t}{\hat{Q}} \right] \right\} & \text{if } t \leq T_S \\ B(q_t) - C(q_t, t) - D(t) & \text{if } t > T_S. \end{cases}$$

(13)

Substituting from (5) and (6) in (13),

$$U(q_t, t) = \theta_0 + \theta_1 q_t - \theta_2 q_t^2 + [\phi_1 t + \phi_2 t^2] q_t - \beta_1 g_t q_t - \beta_2 c_t q_t - D(t) - \max \left\{ 0, \lambda S \cdot \left[ 1 - \frac{\sum_{\tau=1}^t q_{\tau}}{Q} \right] \right\}, \text{ for } t \leq T_S. \quad (14)$$

The right-most term in the utility function, (14), represents the psychological disutility of carrying a mental account of the sunk cost. This disutility continues until the mental account is closed by reaching the cumulative usage target, $\hat{Q}$, or the end of the planning horizon, $T_S$. Drivers may differ in their target usage, $\hat{Q}$. As we shall discuss below, our estimation procedure allows for this (unobserved) heterogeneity. The parameter, $\lambda$, represents the driver’s sensitivity to the sunk cost. We are interested in testing empirically whether $\lambda > 0$.

As above, we assume that the driver is forward-looking, and, in each month, $t$, rationally chooses usage, $q_t$, to maximize $\sum_{\tau=t}^{T_s} U_t$, where $U_t \equiv U(q_t, t)$. In this generalized model, the consumer 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 sunk-cost planning horizon, $T_S$, we calculate the driver’s usage by working backward from the last period, i.e., first $q_{T_S}$, followed by $q_{T_S-1}$, and so on. Differentiating the cumulative expected utility for $t = T_S$,

$$\frac{dU_{T_S}}{q_{T_S}} = \theta_1 - 2\theta_2 q_{T_S} + \phi_1 T_S + \phi_2 T_S^2 - \beta_1 g_{T_S} - \beta_2 c_{T_S} + \frac{\lambda S}{Q} = 0,$$
and hence,

\[ q^*_T = \frac{1}{2\theta_2} \left\{ \theta_1 + \phi_1 T + \phi_2 T^2 - \beta_1 g_T - \beta_2 c_T + \frac{\lambda S}{Q} \right\} . \]

Similarly, differentiating the cumulative expected utility for \( t = T - 1 \),

\[ \frac{dU_{T-1}}{q_{T-1}} = \theta_1 - 2\theta_2 q_{T-1} + \phi_1 [T - 1] + \phi_2 [T - 1]^2 - \beta_1 g_{T-1} - \beta_2 c_{T-1} + \frac{2\lambda S}{Q} = 0, \]

and, so, we have

\[ q^*_{T-1} = \frac{1}{2\theta_2} \left\{ \theta_1 + \phi_1 [T - 1] + \phi_2 [T - 1]^2 - \beta_1 g_{T-1} - \beta_2 c_{T-1} + \frac{2\lambda S}{Q} \right\} . \]

Reasoning recursively, we can show that the optimal usage in month \( t = 1, \ldots, T \) is

\[ q^*_t = \frac{1}{2\theta_2} \left\{ \theta_1 + \phi_1 t + \phi_2 t^2 - \beta_1 g_t - \beta_2 c_t + [T_T - t + 1] \frac{\lambda S}{Q} \right\} . \] (15)

For months, \( t = T + 1, \ldots, T \), the optimal usage is conventionally rational, as characterized in (10). Accordingly, we have

**Proposition 2** With mental accounting for sunk costs, the optimal usage in months, \( t = 1, \ldots, T \), is

\[ q^*_t = \frac{1}{2\theta_2} \left\{ \theta_1 + \phi_1 t + \phi_2 t^2 - \beta_1 g_t - \beta_2 c_t + [T_T - t + 1] \frac{\lambda S}{Q} \cdot 1_{\{t \leq T\}} \right\} , \] (16)

which

(i) increases in the sunk cost, and

(ii) attenuates with time at a rate that increases in the sunk cost.

Notice that, if \( \lambda = 0 \), then (16) simplifies to (10). Hence, the generalized model nests conventionally rational behavior as a special case. 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 that there is no time-dependent marginal benefit, \( \phi_1 = \phi_2 = 0 \). Then, with conventionally rational behavior,
the monthly usage would be constant throughout $T_s$.

- Figure 5 here -

By contrast, comparing (16) with (10), mental accounting for sunk costs would affect behavior in two ways. First, usage increases with the sunk cost (Proposition 2(i)), and second, usage attenuates with time at a rate that increases in the sunk cost (Proposition 2(ii)). Figure 5 illustrates the trajectory of usage for two levels of the sunk cost, $S_1 < S_2$. 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 (assuming that the cumulative usage target is the same).

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 price 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 of mental accounting specifically implies that the effect of the sunk cost attenuates with time, and so, affects the rate at which usage attenuates with time.

Proposition 2(ii) 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 the extent to which cumulative usage meets the target. Specifically, usage in month $t$ is amortized in the driver's utility from month $t + 1$ until the end of the time horizon. Hence, usage in earlier months makes a relatively larger contribution – because it is amortized more times. By contrast, usage in the terminal month contributes only once – to amortization in the terminal month. Accordingly, it is optimal for the driver to use the car relatively more in
the earlier months to the extent that the sunk cost is larger.

This theoretical implication is consistent with two previous empirical studies. In both studies, the sunk cost fallacy attenuated over time. 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.

4 Empirical Strategy

To test Proposition 2 by structural estimation, we set up the econometric model as,

$$q_{it} = \frac{1}{2\theta_2} \left\{ \theta_1 + \phi_1 t + \phi_2 t^2 - \beta_1 g_t - \beta_2 c_t + [T_S - t + 1] \frac{\lambda S_i}{Q_i} \cdot 1_{\{t \leq T_S\}} \right\} + \epsilon_{it}, \quad (17)$$

for individuals $i = 1, \ldots, N$, and where $t$ represents the age of the car in months, $T_S$ is the planning horizon over which the driver mentally accounts for sunk costs, and $\epsilon_{it}$ is a composite error.

Referring to (17), with the available data, we cannot identify the parameter representing the rate of change of marginal benefit, $\theta_2$. We normalize $\theta_2 = 1/2$, and substitute in (17), so that the econometric model simplifies to

$$q_{it} = \theta_1 + \phi_1 t + \phi_2 t^2 - \beta_1 g_t - \beta_2 c_t + [T_S - t + 1] \frac{\lambda S_i}{Q_i} \cdot 1_{\{t \leq T_S\}} + \epsilon_{it}. \quad (18)$$

We assume that the error in (18) comprises two elements,

$$\epsilon_{it} = \nu_i + \xi_{it}, \quad (19)$$

where $\nu_i$ is an individual fixed effect that represents personal taste for driving and captures all unobservable time-invariant attributes of the owner that may influence usage, and $\xi_{it}$ is pure idiosyncratic error. The individual fixed effect controls for individual differences including
selection caused by driving intensity, 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. Households with two cars would use each car less intensively than those with one car.⁹

Our dataset contains cumulative mileage recorded during visits to the service center. Suppose two consecutive visits to the service center by an owner take place at months \( t' \) and \( t'' \) since purchase, with purchase month = 0 and 1, 2, ..., \( t', t' + 1, t' + 2, ..., t'' \). We have data on cumulative mileage at \( t' \) and \( t'' \). From this data we calculate the average mileage per month between \( t' \) and \( t'' + 1, t'' \). On the basis of (18), the average monthly usage between months 1, \( t' \) is as follows:

\[
q_{i,1,t'} = \theta_1 + \phi_1 \frac{t'}{t'} + \phi_2 \frac{t'^2}{t'} - \beta_1 \bar{g}_{t'} - \beta_2 \bar{c}_{t'} + \lambda \bar{A}_{t'} + \bar{\epsilon}_{t'}
\]

with \( A_t = [T_S - t + 1] \frac{S_i}{Q_i} \cdot 1_{(t \leq T_S)} \), and \( \bar{\epsilon}_{t'} = \nu_i + \bar{\xi}_{t'} \). Similarly, the average monthly usage between months \( t' + 1, t'' \) is as follows:

\[
q_{i,t'+1,t''} = \theta_1 + \phi_1 \frac{t'' + 1}{t'' + 1} + \phi_2 \frac{t'^2}{t'} - \beta_1 \bar{g}_{t''} - \beta_2 \bar{c}_{t''} + \lambda \bar{A}_{t''} + \bar{\epsilon}_{t''}
\]

With the available data, we cannot identify the individual fixed effect, \( \nu_i \). So, we cast the econometric model in terms of the difference in the driver’s usage between consecutive

⁹Empirically, the retail price of cars fell from 2001 to 2009, and then rose again. As car prices 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.
service visits,

\[
\Delta q_{i,t'} = q_{i,t'} - q_{i,t''} = \phi_1(t' - t) + \phi_2(t'' - t) - \beta_1(\bar{y}_{it'} - \bar{y}_{it''}) - \beta_2(\bar{c}_{it'} - \bar{c}_{it''}) + \lambda(A_{it'} - A_{it''}) + \zeta_{i,t',t''}
\]  

where, \( \zeta_{i,t',t''} = (\xi_{it'} - \xi_{it''}) \). We assume that \( \xi_{it} \) are i.i.d. \( \mathcal{N}(0, \sigma^2) \), and therefore \( \zeta_{i,t',t''} \) are also \( \mathcal{N}(0, \sigma^2) \). The differencing removes all unobservable time-invariant attributes of the individual that may influence usage, and leaves \( \zeta_{i,t',t''} \) as pure idiosyncratic error.

In essence, our empirical strategy formalizes the intuition of Figure 2. We identify the effect of sunk costs by differences in the rate at which usage declines with age of the car according to differences in the respective sunk costs. The Appendix formally justifies the identification of the mental accounting of sunk costs.

Singapore government policy is very clear about the structure of the ARF and COE rebates, and the policy has been long-standing. In our main specification, we model the sunk cost according to the structure specified by government policy,

\[
S_i = [0.25 \times ARF_i] + [0.2 \times COE_i] + \alpha P_i,
\]

where \( P_i \) is the ex-policy price (wholesale cost, customs duty, goods and services tax, and retail mark-up) as defined in (7) and \( \alpha \in [0, 1] \). This specification allows a fraction, \( \alpha \), of the ex-policy price to be sunk. Therefore, in (22), we use the following:

\[
A_t = \frac{[T - t + 1] \cdot \left\{ [0.25 \times ARF_i] + [0.2 \times COE_i] + \alpha P_i \right\}}{\hat{Q}_i} \cdot 1_{\{t \leq T_s\}}.
\]

This allows us to estimate the driver’s sensitivity to sunk cost, \( \lambda \), and the sunk portion of the ex-policy price, \( \alpha \).

The next issue is that we cannot observe the individual’s target cumulative usage, \( \hat{Q}_i \). So, we need to integrate out \( \hat{Q}_i \) from the econometric model. Accordingly, we estimate the model using the method of maximum simulated likelihood (MSL). MSL involves randomly drawing a large number of values from the distribution of the unobservable \( \hat{Q} \) to calculate
an average likelihood value. Gourieroux and Montfort (1991) show that the MSL estimator is consistent and asymptotically normal as the number of draws, \( M \to \infty \), and number of individuals, \( N \to \infty \).

Our behavioral model of mental accounting is silent on the distribution of the target usage, \( \hat{Q}_i \). Since \( \hat{Q}_i \) is a target quantity of driving (in kilometers) over the planning horizon, its distribution must have positive support. It seems reasonable to assume that the distribution of \( \hat{Q}_i \) is continuous. Specifically, we assume that \( \ln(\hat{Q}_i) \) follows a normal distribution with the mean equal to the sample average of usage, while the variance is estimated along with the parameters of interest. In robustness tests, we allow the mean of the distribution of the target cumulative usage to vary with the size of the car, and let the target cumulative usage follow a gamma distribution.

Therefore, the likelihood function for each individual consumer is

\[
L_i(\eta) = \int \ell_i(\eta, \hat{Q}_i) \Phi(\hat{Q}_i),
\]

where \( \ell_i \) is a function of the vector of parameters to be estimated, \( \eta = (\phi_1, \phi_2, \beta_1, \beta_2, \lambda, \alpha) \), and the target usage, and \( \Phi(\cdot) \) is the lognormal distribution as explained above. We use MSL to evaluate the likelihood function,

\[
\hat{L}_i(\eta) \approx \frac{1}{1000} \sum_{j=1}^{1000} \ell_i(\eta, \hat{Q}_{ij}),
\]

with 1,000 independent draws of \( \hat{Q}_{ij} \) for each individual \( i \). Specifically, we draw \( \ln(\hat{Q}) \) from the standard normal distribution 1,000 times, evaluate the likelihood function at each draw, and then use the average to approximate the likelihood in (26).


\[\text{For each individual } i, \text{ we have multiple observations, one for each service, } m = 1, 2, \ldots, M. \text{ For each service, } m, \text{ let the error density be } f(\eta, m), \text{ where } \eta = (\phi_1, \phi_2, \beta_1, \beta_2, \lambda, \alpha). \text{ Then, individual } i \text{'s likelihood function } \ell_i = f(\eta, 1) \cdot f(\eta, 2) \cdots f(\eta, M). \text{ We integrate out } \hat{Q} \text{ from this expression.}\]
5 Data

Our primary source of data is the authorized dealer for a middle class brand of cars in Singapore. The dealer provided the complete service records of all new cars sold between 2001-2011 under a non-disclosure agreement for the purposes of this study. The cars are different models of the same brand.

Car owners make periodic visits to the authorized dealer for maintenance service. The service records include the following information on each car: date of registration, engine size, service dates, odometer readings, and an indicator of whether the owner of the car was the first or subsequent owner (second-hand car). To protect customer confidentiality, the dealer did not provide any demographic information on the car buyers.

We limited the sample to cars driven by the first owner and less than 120 months in age, which is the lifespan of a COE. Further, to exclude outliers, we further limited the sample to cars within 2 standard deviations of the logarithm of the average monthly usage. Specifically, we exclude cars that have an average monthly usage of less than 534 or above 4,240 kilometers.

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 matched this information by month and engine size to the registration of each car.

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 outliers, we were left with service records of 7,398 cars with 38,105 service visits. 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. The cars in our final sample had average monthly usage ranging between 534 and 4,240 kilometers (or equivalently, annual usage ranging between 4,000 and 31,500 miles).

Finally, to represent the cost of gasoline, we used the Consumer Price Index (CPI) of 98 octane petrol. To represent traffic congestion, we used 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 was 1,569 kilometers. The retail price of the cars ranged between S$110,000 and S$317,400, with an average of S$171,400, while the average ARF and COE premium were S$47,900 and S$21,900 respectively. So, the ARF and COE contributed about 40% of the retail price. The gasoline price index increased from almost 70 in 2001 to over 120 in 2011. Over the same period, the level of congestion increased from about 86 to almost 108 cars per kilometer of road.

– Table 2 here –

6 Results

As a preliminary step, we investigated the relation between cumulative usage and the retail price and policy-related sunk costs. Figure 6 presents locally weighted polynomial regressions of cumulative usage up to 3, 4, and 5 years. Panel (A) suggests that cumulative usage and retail price tended to covary, but the relation was not monotone. In contrast, by panel (B), there seemed to be a clear monotone relation between cumulative usage and the sunk portion of the COE premium and ARF.

– Figure 6 here –

To delve further, we used least squares to regress cumulative usage on the retail car price and policy-related sunk costs, while controlling for age of the car. As Table 3, column (a), reports, the retail price was not significant, which suggests that the retail price did not induce significant selection among buyers by their intended intensity of driving. Table 3, column (b), presents the regression on policy-related sunk costs. Cumulative usage was positively related to the sunk portion of the COE premium, but not significantly related to the sunk portion of the ARF. Overall, the estimates presented in Table 3 are consistent with our behavioral model of mental accounting in which car buyers mentally amortize the sunk cost of purchase relative to some target cumulative usage.

– Table 3 here –
While suggestive, the regressions presented in Figure 6 and Table 3 are simple reduced forms that do not account for confounding explanations, particularly, selection, and do not allow counter-factual policy and managerial analyses. Accordingly, we now turn to structural estimation of the behavioral model. Table 4 presents the estimates.

First, as a baseline, Table 4, column (a), reports a maximum likelihood estimate of consumer behavior according to the conventionally rational model. The coefficient of the price of gasoline, $\beta_1$, is positive and significant, which suggests that drivers are conscious about gas prices. The coefficient of the unit cost of congestion, $\beta_2$, is positive and significant. This result suggests that usage decreased with increases in congestion. With regard to the time-dependent marginal benefit, i.e., the rate of attenuation of usage with age of the car, $\phi_1$ is positive and significant, while $\phi_2$ is negative and significant.\(^{12}\)

\[ \text{Table 4 here} \]

Next, Table 4, column (b), reports a regression of the behavioral model, with mental accounting for sunk costs over a four-year horizon, the sunk cost specified according to the policy structure, (23), and estimated by MSL.\(^{13}\)

The coefficients of gasoline and congestion are similar to those in the estimate of the conventionally rational model. The coefficients of the time-dependent marginal benefit are more than twice as large, which should not surprise as the inclusion of the sunk cost effect, which also varies with the age of the car, would affect estimates of time-dependent marginal benefit parameters.

The coefficient of the mental accounting of sunk cost, $\lambda = 0.486$ (s.d. 0.051), is positive and precisely estimated, while the coefficient of the ex-policy price, $\alpha = 0.023$ (s.d. 0.018), is positive but insignificant.\(^{14}\) These results suggest that car owners did mentally account for the sunk elements of the ARF and COE premium. The results are consistent with

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\(^{12}\)Although the data set comprised 38,105 service records, the first-differencing leading to (22) left 30,707 observations for estimation.

\(^{13}\)Given the structure of the COE and ARF rebates, the sunk cost planning horizon, $T_S$, is likely to be around 5 years. Accordingly, we estimate the behavioral model with $T_S$ varying from 3 to 7 years. Table 4 reports estimates for horizons of 4, 5, and 6 years. The estimates for horizons of 3 and 7 years are similar, and, for brevity, are not reported here.

\(^{14}\)While imprecise, the estimated sunk part of the ex-policy price seems a little low compared to the United States. The average ex-policy price was S$101,600, so, car buyers behaved as if $S$101,600 \times 0.023 = S$2,337 (US$1,855) was sunk. By comparison, in the United States, the average price of a new car is about US$30,000 (FTC 2013), of which about 30% is sunk on purchase (carsdirect.com 2013).
Proposition 2(i) that usage increases in the sunk cost and Proposition 2(ii) that the rate of attenuation of usage with age of the car increases in the sunk cost. Note that our econometric model, (22), is cast in differences, and so, did not allow us to test Propositions 2(i) and 2(ii) separately.

Table 4, column (c), reports a regression of the behavioral model with a five-year horizon. By comparison with the four-year model (log-likelihood of $-20619$), the fit of the five-year model (log likelihood of $-20648$) is worse. The coefficients of gasoline cost, congestion cost, and the time-dependent marginal benefit are quite similar. The sunk cost coefficient, $\lambda = 0.491$ (s.d. 0.040), was also very similar.

As reported in Table 4, column (d), we also estimate the behavioral model with a planning horizon of six years. Upon comparing the various specifications, we prefer the four-year model, reported in Table 4, column (b), because it yields the best fit, as measured by the log likelihood. Comparing the estimates of the conventionally rational model (Table 4, column (a)) and the behavioral model with mental accounting over four years (Table 4, column (b)), we can infer that drivers did not behave in a conventionally rational way. The coefficient of the mental accounting of sunk cost, $\lambda$, is positive and precisely estimated. Further, the model with mental accounting yields a better fit than the conventionally rational model.

To interpret the estimate of the mental accounting of sunk cost, we compute the elasticity of usage with respect to the sunk cost as being $0.164$ (s.d. 0.008). To gauge the significance of this estimate, consider the increase in the COE premium by S$22,491 from S$689 to S$23,180 between February 2009 and February 2010. This raised the sunk cost by $0.2 \times 22,491 = S$4,498. Relative to the average sunk cost, S$16,363, this amounts to a 27.5% increase, and using our estimated elasticity, would be associated with an increase in usage by 4.5% or 70.9 kilometers a month.15

15Consider an increase in the policy-related sunk cost $(0.25 \times ARF + 0.2 \times COE)$ by S$1,000. This would increase usage over a planning horizon of 4 years, with a larger increase in usage in the earlier months and smaller increase in usage in the later months. By Table 4, column (b), $\lambda = 0.486$, so, the total increase in usage would be 756 kilometers over 48 months, which amounts to an average of 15.75 kilometers a month. Dividing by the average monthly usage over the first 48 months, 1,574 kilometers, and multiplying by the average sunk cost, S$16,363, we get the elasticity of 0.164. Note that, in the estimating equation, the costs and price are measured in tens of thousands of Singapore dollars and usage measured in thousands of kilometers.

16Our 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.
We believe that the actual effect of the sunk cost might be larger than this estimate for two reasons. First, 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. Second, 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.

Below, Table 5 presents multiple tests to check the sensitivity of our findings to alternative specifications of sunk costs and target cumulative usage, differences between smaller and larger cars, and COE salience. For convenience, Table 5, column (a), reproduces the preferred estimate from Table 4, column (b).\footnote{In additional robustness tests, we also carry out the MSL with 500 and 750 draws rather than 1000 draws, and estimate (22) by MSL with the target usage following a gamma rather than lognormal distribution. In economic terms, the results are similar to the preferred estimates, and so, for brevity, we do not report them here.}

**Proportionate Sunk Costs**

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 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,

\[ S_i = \rho \cdot \text{Retail price}_i. \]  

(27)

In this robustness check, we use the following in (22):

\[ A_t = \frac{[T - t + 1] \cdot (\rho P_t)}{Q_i} \cdot 1_{[t \leq T_s]}. \]  

(28)

Estimation of model (22) now identifies the product, \( \lambda \rho \), but cannot separately identify
Table 5, column (b), reports the MSL estimate. The estimated coefficient of $\lambda \rho$ is positive and precisely estimated. Importantly, the implied elasticity, 0.177(s.d. 0.013), is fairly close to the preferred estimate.

**Target Cumulative Usage**

Being unable to observe each individual’s target cumulative usage, we stipulate that it is drawn from a lognormal distribution, and then estimate the behavioral model by maximum simulated likelihood. An alternative approach is to use a proxy for the target cumulative usage.

Intuitively, if the COE or ARF is higher, causing the sunk cost of purchase to be higher, the car buyer would aim for a higher target cumulative usage. Hence, a good proxy for any individual’s target cumulative usage is the actual cumulative usage of other people who bought the same model of car at around the same time. The other buyers would incur the same sunk cost, and so, their target cumulative usage should be similar to the particular individual. Indeed, the proxy only works to the extent that car buyers are influenced by sunk costs. We validate the proxy by a simple linear regression of the ratio of the policy-related sunk cost to own cumulative usage on the ratio of the policy sunk cost to average cumulative usage over a 4 year period of others who bought the same model of the car within a one-month window. The proxy is statistically significant ($p < 0.01$) and the regression fit reasonably well ($R^2 = 20.2\%$).

Table 5, column (c), reports a maximum likelihood estimate of (22) with each individual’s target cumulative usage represented by the proxy. The coefficients of the costs of gasoline and congestion and time-dependent marginal benefit are similar to the preferred estimates. The estimated sensitivity to sunk costs, $\lambda = 0.569$(s.d. 0.031), is positive and precisely estimated. It implies the elasticity of usage with respect to sunk cost to be 0.169(s.d. 0.015), which is close to the elasticity based on the preferred specification.

Our preferred estimate stipulates that the distribution of target cumulative usage is the same for all car buyers, which is a fairly standard way of dealing with the unobserved heterogeneity. The next estimate checks the robustness of our findings to this assumption.
The cars in our sample divided roughly equally into two segments at the engine size of 2400 c.c. Since prices correlated with engine size, the division between small and large cars also corresponded to a division between less and more expensive cars. Accordingly, in the next robustness check, we allow the mean target usage to vary, and draw the simulated values for the target cumulative usage from a lognormal distribution, with different means for small (below 2400 c.c.) and large (above 2400 c.c.) cars.

Table 5, column (d), reports the results, estimated by MSL. Compared to the preferred estimate, the main difference is that the implied elasticity of usage with respect to policy sunk cost, 0.192 (s.d. 0.010), is about one-fifth larger compared to the elasticity based on the preferred specification.

COE Salience

Finally, we check whether car owners are influenced by the current COE premium in each month of their driving. To the extent that the current COE premium is lower than the COE premium that they paid on purchase of the car, the COE premium paid might be more salient and induce more driving. We address this possibility of time-varying salience by modifying $A_t$ in the estimation model as follows,

$$A_t = \frac{[T - t + 1] \cdot \left\{ [0.25 \times ARF_i] + [0.2 \times COE_i] + \alpha P_i + \eta[COE_i - COE_t] \right\}}{Q_i} \cdot 1_{\{t \leq T_s\}}.$$  

(29)

where $COE_t$ represents the current COE premium and $\eta$ measures the sensitivity to the salience of the COE premium paid relative to the current COE premium.

Table 5, column (e), reports the MSL estimate. With time-varying salience, the estimated coefficients of the costs of gasoline and congestion, and time-dependent marginal benefit are almost identical to the preferred estimates. The coefficient representing time-varying salience, $\eta = -0.012$ (s.d. 0.020), is positive and not significant, suggesting that the current COE premium did not influence drivers’ usage.
7 Alternative Explanations

Empirically, we find that the rate at which usage attenuates with age of the car increases in the sunk cost. We interpret this relation in terms of mental accounting for sunk costs. But, could the relation be explained by some form of selection?

First, note that the preferred estimate accounts for possible selection by including an individual fixed effect. Specifically, the econometric model, (22), 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 usage or car age.

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

Scaled Marginal Benefit

One alternative explanation is that changes in the retail price induce selection among buyers by their marginal benefit from usage. To address this possibility, we estimate a specification that explicitly allows individuals to differ in their marginal benefit by a scale factor that increases with the retail price. So, a higher retail price would scale up individual marginal benefits and car buyers would drive more.

Specifically, let the marginal benefit be

\[
\exp(\mu P_i) \cdot B'(q_t) = \exp(\mu P_i) \cdot \{\theta_1 - 2\theta_2 q_t + \phi_1 t + \phi_2 t^2\}, \tag{30}
\]

with \( \mu > 0 \) in place of (4). After averaging and differencing, the econometric model simplifies...
\[
\Delta q_{i,t,t'} = q_{i,t,t'} - q_{i,t,t''}
\]
\[
= \phi_1(t'' - t') + \phi_2(t''^2 - t'^2) + \frac{1}{\exp(\mu P_i)} \left\{ -\beta_1(y_{i,t''} + y_{i,t'}) - \beta_2(c_{i,t''} - c_{i,t'}) + \lambda(A_{i,t''} - A_{i,t'}) \right\} + \zeta_{i,t',t''} \tag{31}
\]

Table 5, column (f), reports the regression of (22), estimated by MSL. The signs of the coefficients of gasoline cost, congestion cost, age, and sunk cost are consistent with those in the preferred estimate. Importantly, the estimated coefficient of the sunk cost, \(\lambda\), is positive and precisely estimated. The scale factor, \(\mu = 0.054\) (s.d. 0.003) is positive and significant. Owing to the difference in specification, we cannot directly compare the magnitudes of these and the preferred estimates. However, we can compare the implied elasticities. The implied elasticity from the specification with scaled marginal benefit, 0.167 (s.d. 0.013), which is remarkably close to that implied by the preferred estimate.

**Differential Novelty**

Another possible explanation of the correlation between the rate of attenuation of usage and sunk costs is differential novelty. Suppose that more expensive cars include more fancy features and options, and so, are inherently more novel. Suppose further, that, among people who buy more expensive cars, the effect of novelty wears out faster. Then, the rate of attenuation of usage with age of car would be faster among buyers of the more expensive cars. Since sunk costs are correlated with retail prices, the data would show faster attenuation of usage among the larger, more expensive cars.

To investigate, we estimate the preferred specification separately on cars with small engines (below 2400 c.c.) and those with large engines (above 2400 c.c.). Table 5, columns (g) and (h), report the regressions on the two segments, estimated by MSL. Contrary to the hypothesis of differential novelty effects, there is little difference in the estimated coefficients of the time-dependent marginal benefit, \(\phi_1, \phi_2\), between buyers of small vis-a-vis large cars. The estimated sensitivity to sunk costs among buyers of small cars, 0.429 (s.d. 0.064), is positive and very precise, as is the sensitivity among buyers of large cars, 0.431 (s.d. 0.075).
implied elasticities are close, and in fact, are not statistically different. Apparently, buyers of both small and large cars were influenced by sunk costs, and equally so.

**Demand Shocks**

Yet another possible explanation of the correlation between the rate of attenuation of usage and sunk costs arises from exogenous shocks in the demand for driving. Consider people whose need for driving is random. When the retail price is high, only individuals subject to large positive shocks would buy a car. When the retail price is low, all individuals, whether subject to small or large positive shocks, would buy cars. Over time, driving reverts to the mean. Then, there will be more attenuation with age among cars bought at higher retail prices and higher policy-related sunk costs.

To address this possibility, we analyze the effect of the retail price on the length of car ownership. For the alternative explanation to account for the correlation between the rate of attenuation of usage and sunk costs, the individuals subject to large positive demand shocks must keep their cars at least as long as those subject to small shocks and until the driving needs of both segments revert to the mean.

Our data-set does not explicitly include information on the length of car ownership. We infer that the owner sold the car if it was not serviced for 24 months or more, and stipulate the length of car ownership to be the age at the last recorded service. Table 6 reports regressions of the length of car ownership (in months) on the retail price and policy-related sunk costs. All variables are specified in logarithms, but, for brevity, we omit mention of the logarithms in the discussion.

Table 6, column (a), reports the estimate of the regression of the length of car ownership on the retail price. Apparently, the length of ownership was not significantly related to the length of ownership. In Table 6, column (b), we break down the retail price into the three components – the COE premium and ARF, and the ex-policy price. The striking result is that the length of ownership is negatively correlated with the COE premium. This result is quite intuitive: car owners who paid a higher COE premium would get a larger refund from de-registration. To the extent that a large demand shock induced an individual to buy a
car at a high retail price (and large COE premium), the large COE premium would give the owner greater incentive to de-register as the need for driving diminishes.\footnote{The estimated coefficients of a regression on the sunk parts of the COE premium and ARF are the same as in column (b). The reason is that the sunk part of the COE premium is 20\%, and so, the logarithm of the sunk part is just the logarithm of the COE premium plus a constant, and, similarly, for the sunk part of the ARF.}

8 Implications for Public Policy and Management

Our findings of the sunk cost effect have implications for public policy and management and pricing of durable goods. In August 2005, after almost 2000 Americans had died in Iraq, U.S. president George Bush famously declared, “We owe them something. We will finish the task that they gave their lives for”. Organizational theorists interpret such “escalation of commitment” as rationalizing the decision-maker’s earlier investments (Staw 1976; Staw and Hoang 1995; McCarthy et al. 1993; Staw et al. 1997; Barron et al. 2001). To the extent that sunk costs affect subsequent choices – whether among national leaders or business executives – our findings suggest a need for more effort in debiasing and self-correction.

Our results apply particularly to road transport policy. Historically, the Singaporean government managed traffic congestion through pricing of road usage and taxing car ownership. By design, the Additional Registration Fee (ARF) and Certificate of Entitlement (COE) embodied 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 February 2009 and February 2010, the quota of COEs in categories “B” and “E” fell by one-third from 3818 to 2569.\footnote{The Singapore government issues COEs in five categories. The two categories relevant to the brand of cars in our data-set are categories “B” and “E”.} The quota reduction coupled with growth of the Singapore economy resulted in the COE premium increasing sharply from S$689 to S$23,180 (a dramatic increase of S$22,491). This increased the sunk cost of buying a car by $0.2 \times 22,491 = S$4,498. Using our preferred estimate, this increase in the sunk cost would be associated with an increase in monthly usage by 70.9 kilometers.

Hence, absent any other policy changes, the reduction in the COE quota would have affected 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 1.96 million kilometers a month. On the other hand, 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 0.18 million kilometers a month. So, mental accounting for sunk costs would give rise to an economically significant countervailing effect.

The effect of sunk costs on drivers is economically significant, at least as perceived by the Singapore government:

“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 electronic road pricing) to manage the demand for road space” (Leong and Lew 2009).

In recent years, the reduction in COE quotas has resulted in sharp increases in the COE premium, which have outweighed reductions in the ARF. Our estimated model allows policymakers to systematically evaluate the net effect of the increase in COE premium and the reduction in the ARF on driving.

To the extent that managers, being human, are also influenced by sunk costs, our results also 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, manufacturers such as Tetrapak and Hewlett-Packard sell machinery and then also sell consumables to buyers of their equipment.

Based on consumer psychology, 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 this ‘razor-blade” strategy may be suboptimal because customers who purchase at a low price may end up using the

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20Leong 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.
platform less and hence purchasing less consumables. This implication resonates with the previous literature on mental accounting (Thaler 1990: 49-50).

9 Concluding Remarks

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

Then, we took the model to a proprietary panel data-set of 7,398 cars between 2001-2011 in Singapore, which is the world’s most expensive car market. Through structural estimates, we found 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 4 years of the car ownership. Our results were robust to alternative explanations in terms of selection, the specification of sunk costs and target cumulative usage, the type of car, and salience of sunk costs.

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 study was based on Singapore data, we believe that similar results apply to car buyers in other countries, and more generally, the effect of sunk costs on usage in other repeated situations. Our reason is that, in one specification, we framed the sunk cost simply as a proportion of the retail price. That estimate did not depend on the particular sunk-cost structure of the ARF and COE premium. Based on our estimates, we expect that, in other markets, usage of durable goods would increase with the sunk element of the price and attenuate over a certain planning horizon, and that the rate of attenuation would increase 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 sunk costs on consumer behavior. The disparity in findings may be due to differences in context. We focused on 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. There was no random assignment of sunk costs to different individuals. Hence, 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 contrast between our results and those of Ashraf et al. (2010) and Cohen and Dupas (2010)? Besides the passage 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


Appendix

Generalizing (14), 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,
\[
\frac{dq^*_t}{dR} = \frac{\partial q^*_t}{\partial R}(t, c_t, g_t, R, S) + \frac{\partial q^*_t}{\partial S}(t, c_t, g_t, R, S) \cdot \frac{dS}{dR}.
\]
(32)

In (32), 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, (32), 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 \textit{age of the car}. Differentiating (32) with respect to \( t \),
\[
\frac{d^2 q^*_t}{dRdt} = \frac{\partial^2 q^*_t}{\partial R^2}(t, c_t, g_t, R, S) + \frac{\partial^2 q^*_t}{\partial S^2}(t, c_t, g_t, R, S) \cdot \frac{dS}{dR} + \frac{\partial q^*_t}{\partial S}(t, c_t, g_t, R, S) \cdot \frac{d^2 S}{dRdt}.
\]
(33)

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, (33) simplifies to
\[
\frac{d^2 q^*_t}{dRdt} = \frac{\partial^2 q^*_t}{\partial S^2}(t, c_t, g_t, R, S) \cdot \frac{dS}{dR}.
\]
(34)

Using the data, we estimate the left hand side of (34), and then integrate over \( t \) to obtain
\[
\frac{\partial q^*_t}{\partial S}(t, c_t, g_t, R, S) \cdot \frac{dS}{dR}.
\]
(35)

Government policy specifies the relation between sunk costs and the retail price, \( dS/dR \), and so, (35) identifies the parameter, \( \partial q^*_t/\partial S \), which characterizes the sunk cost effect.
Figure 1. Monthly usage, retail car price, and policy-related sunk cost

(A)

(B)

Notes: For the most popular model in the sample (2,726 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 over life of car

Note: For the most popular model in the sample (2,726 cars). Legends present year and average policy-related sunk costs (S$) of cars bought in that year. Monthly average usage was interpolated for the months between successive service records.

Figure 3. COE and ARF rebate structure
Figure 4. Price and costs

Notes: For the most popular model in the sample (2,726 cars). Price and costs in S$.

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

Notes: For the entire sample (7398 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$’000). Panel B depicts regressions of cumulative usage up to 3 years (lower graph), 4 years (middle graph), and 5 years (upper graph) on the sunk portion of COE premium and ARF (in S$’000).
### Table 1. COE premium

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>(a) COE premium ($’000)</th>
<th>(b) Change in COE premium ($’000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>260.332** (69.236)</td>
<td>0.575 (0.448)</td>
</tr>
<tr>
<td>COE quota (‘000)</td>
<td>-4.095*** (0.777)</td>
<td></td>
</tr>
<tr>
<td>Change in COE quota</td>
<td></td>
<td>-2.345** (1.042)</td>
</tr>
<tr>
<td>CPI fuel index</td>
<td>-0.223** (0.102)</td>
<td>-0.063 (0.133)</td>
</tr>
<tr>
<td>Change in CPI fuel index</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cars per km</td>
<td>-2.954*** (0.778)</td>
<td></td>
</tr>
<tr>
<td>Change in cars per km</td>
<td></td>
<td>-1.988* (1.159)</td>
</tr>
<tr>
<td>Quarterly GDP ($’000)</td>
<td>1.442*** (0.377)</td>
<td>0.575 (0.448)</td>
</tr>
<tr>
<td>Change in quarterly GDP</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year – 2004</td>
<td>-5.208** (2.451)</td>
<td></td>
</tr>
<tr>
<td>Year – 2005</td>
<td>-11.812** (5.144)</td>
<td></td>
</tr>
<tr>
<td>Year – 2006</td>
<td>-11.933 (8.110)</td>
<td></td>
</tr>
<tr>
<td>Year – 2007</td>
<td>-6.316 (13.112)</td>
<td></td>
</tr>
<tr>
<td>Year – 2008</td>
<td>5.788 (15.014)</td>
<td></td>
</tr>
<tr>
<td>Year – 2009</td>
<td>-0.357 (16.789)</td>
<td></td>
</tr>
<tr>
<td>Year – 2010</td>
<td>10.991 (19.624)</td>
<td></td>
</tr>
<tr>
<td>Year – 2011</td>
<td>27.901 (20.876)</td>
<td></td>
</tr>
<tr>
<td>Quarter fixed effects</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Number of observations</td>
<td>102</td>
<td>101</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>93.9%</td>
<td>7.5%</td>
</tr>
</tbody>
</table>

### Table 2. Summary statistics

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>Unit</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Usage</td>
<td>‘000 kilometers per month</td>
<td>1.569</td>
<td>0.53</td>
<td>0.53</td>
<td>4.24</td>
</tr>
<tr>
<td>Retail price</td>
<td>S$’000</td>
<td>171.4</td>
<td>31.1</td>
<td>110.0</td>
<td>317.4</td>
</tr>
<tr>
<td>ARF</td>
<td>S$’000</td>
<td>47.9</td>
<td>9.9</td>
<td>30.5</td>
<td>93.0</td>
</tr>
<tr>
<td>COE premium</td>
<td>S$’000</td>
<td>21.9</td>
<td>9.0</td>
<td>0.7</td>
<td>68.5</td>
</tr>
<tr>
<td>Gasoline price</td>
<td>2006 January = 100</td>
<td>94.80</td>
<td>16.30</td>
<td>69.10</td>
<td>126.60</td>
</tr>
<tr>
<td>Congestion</td>
<td>Cars per kilometer</td>
<td>95.30</td>
<td>8.20</td>
<td>85.80</td>
<td>107.60</td>
</tr>
</tbody>
</table>

Note: US$1 = S$1.26 (December 17, 2013).

### Table 3. Cumulative usage, retail car price, and policy-related sunk costs

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>(a) Retail price</th>
<th>(b) Policy-related sunk costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price (S$’000)</td>
<td>0.013</td>
<td>1.409***</td>
</tr>
<tr>
<td>COE sunk cost</td>
<td></td>
<td>(0.009)</td>
</tr>
<tr>
<td>ARF sunk cost</td>
<td></td>
<td>-0.001</td>
</tr>
<tr>
<td>(0.169)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (months)</td>
<td>1.674***</td>
<td>1.775***</td>
</tr>
<tr>
<td>(0.068)</td>
<td>(0.071)</td>
<td></td>
</tr>
<tr>
<td>Age-square</td>
<td>-0.002***</td>
<td>-0.003***</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-2.395</td>
<td>-8.549***</td>
</tr>
<tr>
<td>(2.362)</td>
<td>(2.153)</td>
<td></td>
</tr>
<tr>
<td>Cars</td>
<td>7,398</td>
<td>7,398</td>
</tr>
<tr>
<td>R-squared</td>
<td>54.1%</td>
<td>54.5%</td>
</tr>
</tbody>
</table>

Notes: For the entire sample (7398 cars). Ordinary least squares regressions; dependent variable: Cumulative usage (‘000 km) at last observed service; Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).
Table 4. Effect of sunk cost on car usage

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>(a) No sunk cost effect</th>
<th>(b) Horizon: 4 years (preferred)</th>
<th>(c) Horizon: 5 years</th>
<th>(d) Horizon: 6 years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gasoline cost, $\beta_1$</td>
<td>0.001**</td>
<td>0.001**</td>
<td>0.001**</td>
<td>0.001**</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td>Congestion cost, $\beta_2$</td>
<td>0.008***</td>
<td>0.013***</td>
<td>0.012***</td>
<td>0.011***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Age, $\phi_1 \times 10$</td>
<td>0.136***</td>
<td>0.309***</td>
<td>0.249***</td>
<td>0.212***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Age squared, $\phi_2 \times 100$</td>
<td>-0.014***</td>
<td>-0.024***</td>
<td>-0.018***</td>
<td>-0.015***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Sunk cost, $\lambda$</td>
<td>0.486***</td>
<td>0.491***</td>
<td>0.426***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.040)</td>
<td>(0.048)</td>
<td></td>
</tr>
<tr>
<td>Sunk part of ex-policy price, $\alpha$</td>
<td>0.023</td>
<td>0.0001</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.0001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>No. of service records</td>
<td>30707</td>
<td>30707</td>
<td>30707</td>
<td>30707</td>
</tr>
<tr>
<td>No. of cars</td>
<td>7398</td>
<td>7398</td>
<td>7398</td>
<td>7398</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-20676</td>
<td>-20619</td>
<td>-20648</td>
<td>-20664</td>
</tr>
<tr>
<td>Elasticity</td>
<td>n.a.</td>
<td>0.164***</td>
<td>0.158***</td>
<td>0.127***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.013)</td>
<td>(0.014)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: For the entire sample (7398 cars); Dependent variable is first difference of usage (‘000 km per month); Gasoline cost is estimated by CPI-fuel/10 and congestion cost is estimated 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$0’000. Column (a): Conventionally rational behavior, estimated by maximum likelihood. Columns (b)-(d): Model of mental accounting for sunk costs, specified according to COE and ARF rebate policy, with horizons of 4, 5, and 6 years; estimated by maximum simulated likelihood regression, with lognormal distribution of target usage. Robust standard errors computed by the Huber sandwich estimator in parentheses (*** p<0.01, ** p<0.05, * p<0.1). The asymptotic covariance matrix computed by the Huber sandwich estimator, $\hat{V} = (-A)^{-1}B(-A)$ where $A = L''(\hat{\eta})$ and $B = \sum_{i=1}^{l} s_i(\hat{\eta})' s_i(\hat{\eta})$, where $L$ is the log-likelihood function and $s_i$ is the score function, for car buyers $i = 1, ..., l$ (*** p<0.01, ** p<0.05, * p<0.1).
Table 5. Robustness checks

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>(a) Preferred estimate</th>
<th>(b) Sunk cost proportional to retail price</th>
<th>(c) Proxy for target usage</th>
<th>(d) Heterogeneous target usage</th>
<th>(e) COE salience</th>
<th>(f) Scaled marginal benefit</th>
<th>(g) Small cars</th>
<th>(h) Large cars</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gasoline cost, $\beta_1$</td>
<td>0.001**</td>
<td>0.001**</td>
<td>0.001**</td>
<td>0.001**</td>
<td>0.001**</td>
<td>0.001**</td>
<td>0.001***</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0005)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>Congestion cost, $\beta_2$</td>
<td>0.013***</td>
<td>0.008***</td>
<td>0.012***</td>
<td>0.013***</td>
<td>0.017***</td>
<td>0.012***</td>
<td>0.014***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Age, $\phi_1 \times 10$</td>
<td>0.309***</td>
<td>0.291***</td>
<td>0.303***</td>
<td>0.297***</td>
<td>0.308***</td>
<td>0.431***</td>
<td>0.314***</td>
<td>0.323***</td>
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<tr>
<td></td>
<td>(0.012)</td>
<td>(0.013)</td>
<td>(0.010)</td>
<td>(0.011)</td>
<td>(0.012)</td>
<td>(0.017)</td>
<td>(0.022)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Age squared, $\phi_2 \times 100$</td>
<td>-0.024***</td>
<td>-0.024***</td>
<td>-0.023***</td>
<td>-0.024***</td>
<td>-0.032***</td>
<td>-0.024***</td>
<td>-0.025***</td>
<td></td>
</tr>
<tr>
<td>Sunk cost, $\lambda$</td>
<td>0.486***</td>
<td>0.569***</td>
<td>0.502***</td>
<td>0.690***</td>
<td>1.248***</td>
<td>0.429***</td>
<td>0.431***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.031)</td>
<td>(0.046)</td>
<td>(0.041)</td>
<td>(0.094)</td>
<td>(0.064)</td>
<td>(0.075)</td>
<td></td>
</tr>
<tr>
<td>Sunk part of ex-policy price, $\alpha$</td>
<td>0.023</td>
<td>0.0001</td>
<td>0.004</td>
<td>0.026</td>
<td>0.170***</td>
<td>0.083**</td>
<td>0.040</td>
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<tr>
<td>Marginal benefit scale factor, $\mu$</td>
<td>0.018</td>
<td>(0.0001)</td>
<td>(0.013)</td>
<td>(0.019)</td>
<td>(0.021)</td>
<td>(0.039)</td>
<td>(0.028)</td>
<td></td>
</tr>
<tr>
<td>Sunk cost, $\lambda \rho$</td>
<td>0.050***</td>
<td></td>
<td></td>
<td></td>
<td>0.054***</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Salience effect, $\eta$</td>
<td>0.012</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>No. of observations</td>
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<td>30707</td>
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<td>30707</td>
<td>30707</td>
<td>15056</td>
<td>15651</td>
</tr>
<tr>
<td>No. of cars</td>
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<td>7398</td>
<td>7398</td>
<td>7398</td>
<td>7398</td>
<td>7398</td>
<td>3621</td>
<td>3777</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-20619</td>
<td>-20627</td>
<td>-20621</td>
<td>-20623</td>
<td>-20619</td>
<td>-20582</td>
<td>-9876</td>
<td>-10736</td>
</tr>
<tr>
<td>Elasticity</td>
<td>0.164***</td>
<td>0.177***</td>
<td>0.169***</td>
<td>0.192***</td>
<td>0.233***</td>
<td>0.167***</td>
<td>0.135***</td>
<td>0.156***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.013)</td>
<td>(0.015)</td>
<td>(0.010)</td>
<td>(0.014)</td>
<td>(0.013)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
</tbody>
</table>

Notes: Dependent variable is first difference of usage (‘000 km per month); Gasoline cost is estimated by CPI-fuel/10 and congestion cost is estimated 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$0’000. Estimated by maximum simulated likelihood regression, with lognormal distribution of target usage (except column (d)) and robust standard errors computed by the Huber sandwich estimator in parentheses (** p<0.01, * p<0.05, * p<0.1); Column (a): Preferred estimate; Column (b): Sunk cost proportional to retail price (rather than according to COE and ARF rebates); Column (c): Target usage proxied by average cumulative usage up to 4 years of others who bought the same model of the car within a 1-month window, estimated by maximum likelihood; Column (d): Estimated by MSL regression, with different means of target usage for small and large cars; Column (e): With time varying salience, measured by difference between current COE premium and COE premium paid on purchase; Column (f): Marginal benefit inflated by scale factor depending on retail price; Columns (g)-(h): Separate regressions for small and large cars.
Table 6. Length of car ownership, retail car price, and policy-related sunk costs

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>(a)</th>
<th>(b)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln(Retail price)</td>
<td>-0.044</td>
<td>0.117*</td>
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<tr>
<td></td>
<td>(0.048)</td>
<td>(0.065)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(Ex-policy price)</td>
<td></td>
<td>-0.076***</td>
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<tr>
<td></td>
<td></td>
<td>(0.012)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(COE premium)</td>
<td></td>
<td>-0.069</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.072)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(ARF)</td>
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<td></td>
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<tr>
<td>Constant</td>
<td>5.080***</td>
<td>4.778***</td>
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</tr>
<tr>
<td></td>
<td>(0.362)</td>
<td>(0.329)</td>
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<tr>
<td>Fixed effects for year</td>
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<td>Yes</td>
<td></td>
<td></td>
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<tr>
<td>Fixed effects for quarter</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
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<tr>
<td>Fixed effects for engine size</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Observations</td>
<td>6,072</td>
<td>6,072</td>
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<tr>
<td>R-squared</td>
<td>0.538</td>
<td>0.542</td>
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</tbody>
</table>

Notes: Dependent variable: Logarithm of car ownership in months. Column (a): Regression on retail price; Column (b): Regression on components of retail price.