

Sunk Cost Fallacy in Driving the World's Costliest Cars

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Abstract

Do decision-makers suffer from the sunk cost fallacy in high-stakes situations? We develop a behavioral model of usage of a durable good with mental accounting for sunk costs. It predicts that the usage increases with the sunk cost, and attenuates with time at a rate that increases with the sunk cost. The model nests conventionally rational behavior as a special case.

We take the model to a panel of 6,474 cars between 2001-2011 in Singapore. During that period, the sunk cost involved in a new car purchase varied substantially with the continuing government policy. We found robust evidence of a sunk cost fallacy. The elasticity of usage with respect to the sunk cost was $0.563(\pm 0.072)$. An increase in the sunk cost by S\$4,500 (the outcome of government policy between 2009 and 2010) would have been associated with an increase in monthly usage by 147 kilometers or 8.8%. Our results were robust to various checks including alternative controls for selection, differences in specification, and allowing for heterogeneity in engine size and target cumulative usage.

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

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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 (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: attendance was highest in the month in which the members paid their half-yearly installment, and then declined with time. In a more recent study, Just and Wansink (2011) conducted a field experiment and found that the diners consumed less at an all-you-can-eat-pizza restaurant when there was a discount on the price.

However, in other settings, consumers did not appear to be suffering from the sunk cost fallacy. In a large-scale Zambian field experiment, Ashraf et al. (2010) gave consumers unannounced random discounts on sales of Clorin, a chemical to treat drinking water. Differences in the amount paid did not affect the consumers’ use of the chemical to treat water. Further, in laboratory experiments, Phillips et al. (1991) and Friedman et al. (2007) did not find any evidence of sunk cost fallacy.

Thus far, studies of the sunk cost fallacy have focused on consumer situations of relatively low stakes and yielded conflicting results. The different results might arise because of differences in the saliency of the sunk cost in the various experimental settings. By contrast, when buying big-ticket items such as cars, the sunk costs would surely be more salient. Since

the cost of mistakes would be larger, consumers might invest more effort to correct irrational biases in decision-making. On the other hand, the saliency of the sunk costs might lead consumers to pay more attention to the sunk costs, resulting in an even larger influence on behavior.¹

Here, we investigate whether consumers are influenced by sunk costs in high stakes situations. Based on the 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 consumer 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 cannot fully self-correct) decision bias even when the cost of mistakes is large.

Car usage is an attractive setting for investigation of the effect of mental accounting on behavior in a high-stakes situation. People have many years of experience with cars, and usage is sustained over long periods of time. In seventeen 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 the context of a durable good, we first develop a behavioral model of utility maximization to understand how sunk costs may influence usage over time. The model assumes that car buyers mentally account

¹Many 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 two-stage estimation, the effect of prior decisions was significant but very small.

for the sunk cost of a new car by amortizing the sunk cost relative to the target cumulative usage over the life of a car (Gourville and Soman 1998; Thaler 1999). 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 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 6,474 units of one premium 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 average retail price of the cars in the panel and the monthly usage by vintage of car over the period of study for the two most popular models. Evidently, people who bought cars when prices were high tended to use their cars relatively more. The average retail price of cars fluctuated substantially, rising from about S\$174,000 (US\$142,000) in 2001 to a peak of S\$185,000 (US\$152,000) in 2003, and then declining to a low of S\$158,000 (US\$130,000) in 2009, and finally, rising sharply to S\$205,000 (US\$168,000) in 2011.² Monthly usage followed a similar trajectory, rising to a peak in 2003, and then declining until 2007. While the retail price rose slightly from 2007-08, the usage increased sharply and then fell back to a low in 2009, before rising again. Below, we explain that, by government policy, the sunk costs incurred in a new car purchase were closely related to the retail price. Accordingly, Figure 1 also implies that people who bought cars when sunk costs were larger tend to use their cars relatively more.

– Figure 1 here –

However, the correlation in Figure 1 could 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 car prices would be associated with more car usage. To distinguish selection from mental accounting for sunk costs, we draw a key implication from

²Converted at US\$1 = S\$1.22. We stress that, in Europe and the United States, this brand of cars would be considered “middle class”.

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 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.³ The retail price fell steadily from 2003 until 2006. The lower was the retail price, the lower the monthly usage tended to be, at all ages of car. Usage attenuated with age of the car, with an especially steep decline in the first 12 months. More importantly, consistent with the central implication of the behavioral model, the lower was the retail price, the slower was the rate at which usage attenuated with time.

– Figure 2 here –

Our empirical strategy explicitly addressed the alternative explanation of selection effects in two other ways. One was to estimate the model in terms of first differences of usage, rather than the levels of usage. Differencing would wipe out any non-usage and non-time varying heterogeneity among car buyers, such as that arising from selection. All of our estimates were cast in terms of first differences. The other way of addressing selection was to explicitly model the marginal benefit from usage as varying according to the retail price of the car. Our results were robust to this alternative specification.

Our structural estimates suggested that the elasticity of usage with respect to the sunk cost of a car was $0.563(\pm 0.072)$. An increase in the sunk cost by S\$4,498 (the outcome of continuing government policy between 2009 and 2010) would have been associated with an increase in monthly usage by 147 kilometers or 8.8%. This effect is robust to various checks including alternative controls for selection and differences in specification and model.

In the remainder of this paper, Section 2 describes Singapore government policies towards car ownership and usage and Section 3 presents a behavioral model of mental accounting for sunk costs. Section 4 presents the empirical strategy, Section 5 introduces the data, and Section 6 reports structural estimates of the behavioral model. Section 7 discusses implications of our findings for policy and management, while Section 8 concludes.

³Figure 2 focuses on usage between months 6 and 36. In the first few months, usage might be affected by spurious factors, for instance, some cars were used for test drives and others were assigned to international events before being sold to end-users.

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 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 targeted 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.⁴

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:

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

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. As already mentioned, 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\$205,000 (US\$168,000).

⁴No cars are manufactured in Singapore. Since all are imported, the import price equals the wholesale cost.

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 would be pro-rated linearly by the days remaining until the car reached 10 years of age. The COE expires after 10 years, so, either the owner had to buy a new COE or ship the car out of Singapore.

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 would be 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.

– Figure 3 here –

Consequently, in Singapore, the purchase of a new car involves two policy-related sunk costs:⁵

- Within the first 24 months, 20% of the COE premium would be sunk. This cost would not vary with usage or time. 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 time but not usage.
- Within the first 60 months, 25% of ARF would be sunk. This cost would not vary with usage or time. 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.

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

⁵In the behavioral model, we also allow for a sunk cost on the car itself, unrelated to government policy.

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\$3,100, compared with the mean retail price of S\$158,138. We exploit this variation to identify the effect of sunk costs on car usage.

– Figure 4 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 driver behavior for structural estimation. 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 so, 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, $1, \dots, T$. In each month, t , let the driver's utility be

$$U(q_t, t) = B(q_t, t) - C(q_t, t) - D(t), \quad (2)$$

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,

$$B(q_t) = \theta_0 + [\theta_1 + \phi(t)]q_t - \theta_3q_t^2, \quad (3)$$

or equivalently the marginal benefit from usage,

$$B'(q_t) = \theta_1 + \phi(t) - 2\theta_3q_t. \quad (4)$$

We assume that $\theta_0, \theta_1, \theta_3, \phi(\cdot) > 0$, and are such that the marginal benefit, $B'(\cdot) > 0$, and the marginal benefit diminishes with age and usage, $B''(\cdot) < 0$.⁶

The function, $\phi(\cdot)$, represents the effect of time on marginal benefit. The user's marginal benefit declines with time for two reasons. One is a taste for novelty – newer cars provide more benefit. 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). Referring to Figure 2, we assume that

$$\phi = e^{-\theta_2 t}, \quad (5)$$

where $\theta_2 > 0$.

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

$$C(q_t, t) = \beta_1 g_t q_t + \beta_2 c_t q_t, \quad (6)$$

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

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

⁶The quadratic functional form, (3), may be interpreted as a Taylor series approximation of a more general benefit function that exhibits diminishing marginal benefit.

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:

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

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, and $\delta_1(t)$ and $\delta_2(t)$ are the depreciation functions of the ARF and COE premium with time.

Substituting above, the consumer’s utility is

$$U(q_t, t) = \theta_0 + \theta_1 q_t + e^{-\theta_2 t} q_t - \theta_3 q_t^2 - \beta_1 g_t q_t - \beta_2 c_t q_t - D(t). \quad (9)$$

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

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

$$q_t^* = \frac{1}{2\theta_3} [\theta_1 + e^{-\theta_2 t} - \beta_1 g_t - \beta_2 c_t]. \quad (10)$$

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

$$\sum_{\tau=t}^T U_\tau = \sum_{\tau=t}^T [\theta_0 + \theta_1 q_t + e^{-\theta_2 t} q_t - \theta_3 q_t^2 - \beta_1 g_t q_t - \beta_2 c_t q_t - D(t)]. \quad (11)$$

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

$$q_t^* = \frac{\theta_1 + e^{-\theta_2 t} - \beta_1 g_t - \beta_2 c_t}{2\theta_3}, \quad (12)$$

for all t .

By Proposition 1, the optimal usage decreases with time due to the novelty effect. 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.

3.2 Mental Accounting for Sunk Costs

Next, we generalize the model to allow for the sunk cost fallacy. We suppose that the driver's utility is a function of both usage and mental accounting for the sunk cost. Specifically, the consumer amortizes the sunk cost, S , by the actual cumulative usage, Q_t , relative to some target cumulative usage, \hat{Q} , over the entire time horizon (Gourville and Soman 1998; Thaler 1999). Accordingly, we generalize the utility in month t as,

$$\begin{aligned} U(q_t, t) &= B(q_t) - C(q_t, t) - D(t) - \max \left\{ 0, \lambda S \cdot \left[1 - \frac{Q_t}{\hat{Q}} \right] \right\} \\ &= \theta_0 + \theta_1 q_t + e^{-\theta_2 t} q_t - \theta_3 q_t^2 - \beta_1 g_t q_t - \beta_2 c_t q_t - D(t) - \max \left\{ 0, \lambda S \cdot \left[1 - \frac{\sum_1^t q_t}{\hat{Q}} \right] \right\}. \end{aligned} \quad (13)$$

The right-most term in the utility function, (13), 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} . Drivers may differ in their target usage, \hat{Q} . As we shall discuss below, our estimation procedure allows for this (unobserved) heterogeneity. The parameter, λ , represents the driver's sensitivity to sunk cost. We are interested to test empirically the presence of the sunk cost fallacy, i.e., 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 $\sum_{\tau=t}^T U_t$, where $U_t \equiv U(q_t, t)$. In this generalized model, the driver takes account the effect of q_t on future utility through the cumulative usage in month t , $Q_t = \sum_{\tau=1}^t q_t$.

We calculate the driver's usage by working backward, i.e., first q_T^* , followed by q_{T-1}^* , and so on. Differentiating the cumulative expected utility for $t = T$,

$$\frac{dU_T}{dq_T} = \theta_1 + e^{-\theta_2 T} - 2\theta_3 q_T^* - \beta_1 g_T - \beta_2 c_T + \frac{\lambda S}{\hat{Q}} = 0,$$

and hence,

$$q_T^* = \frac{1}{2\theta_3} \left[\theta_1 + e^{-\theta_2 T} - \beta_1 g_T - \beta_2 c_T + \frac{\lambda S}{\hat{Q}} \right].$$

Similarly, differentiating the cumulative expected utility for $t = T - 1$,

$$\frac{dU_{T-1}}{dq_{T-1}} = \theta_1 + e^{-\theta_2 [T-1]} - 2\theta_3 q_{T-1}^* - \beta_1 g_{T-1} - \beta_2 c_{T-1} + \frac{2\lambda S}{\hat{Q}} = 0,$$

and, so, we have

$$q_{T-1}^* = \frac{1}{2\theta_3} \left[\theta_1 + e^{-\theta_2[T-1]} - \beta_1 g_{T-1} - \beta_2 c_{T-1} + \frac{2\lambda S}{\hat{Q}} \right].$$

Reasoning recursively, we can show that

Proposition 2 *With mental accounting for sunk costs, the optimal usage in month $t = 1, \dots, T$ is*

$$q_t^* = \frac{1}{2\theta_3} \left\{ \theta_1 + e^{-\theta_2 t} - \beta_1 g_t - \beta_2 c_t + [T - t + 1] \frac{\lambda S}{\hat{Q}} \right\}, \quad (14)$$

which

(i) *increases in the sunk cost, and*

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

Notice that, if $\lambda = 0$, then (14) 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 and that there is no novelty effect, i.e., g_t, c_t are time-invariant and $\theta_2 = 0$. Then, with conventionally rational behavior, the monthly usage would be constant throughout the life of the car (assumed to be 120 months).

– Figure 5 here –

By contrast, comparing (14) 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 over time at a rate that increases with 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)). When the price of new cars is higher, people who plan to drive less would be less likely to buy cars, and so, the population of car owners would be comprised of relatively more intensive drivers. Hence, a higher retail price would be associated with higher usage, even in the absence of any sunk cost fallacy.

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.

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 (13), in each month, as the consumer 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 consumer 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 only contributes once, to amortization in the terminal month. Accordingly, it is optimal for the consumer 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 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

The model of mental accounting for sunk costs is cast in terms of time from the purchase of the car to the end of ownership. However, our data set comprises cars purchased at different dates, so, we must distinguish between calendar time and age of the car. Hence, for purposes of structural estimation, we set up the econometric model as,

$$q_{it} = \frac{1}{2\theta_3} \left\{ \theta_1 + e^{-\theta_2 t} - \beta_1 g_t - \beta_2 c_t + [T - t + 1] \frac{\lambda S_i}{\hat{Q}_i} \right\} + \epsilon_{it}, \quad (15)$$

for individuals $i = 1, \dots, N$, and $t = 1, \dots, 120$, where t represents the age of the car in months, and where ϵ_{it} is a composite error.

Referring to (15), with the available data, we cannot identify the parameter representing the rate of change of marginal benefit, θ_3 . We normalize $\theta_3 = 1/2$, and substitute in (15), so that the econometric model simplifies to

$$q_{it} = \theta_1 + e^{-\theta_2 t} - \beta_1 g_t - \beta_2 c_t + [T - t + 1] \frac{\lambda S_i}{\hat{Q}_i} + \epsilon_{it}. \quad (16)$$

We assume that the error in (16) comprises two elements,

$$\epsilon_{it} = \nu_i + \xi_{it}, \quad (17)$$

where ν_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 ξ_{it} is pure idiosyncratic error. The individual fixed effect would control for individual differences in driving intensity, and in particular, those causing selection effect in the model, as higher car prices selectively screen out those who plan to drive less intensively. The individual fixed effect would also control for differences between first and second cars. Households with two cars would use each car less intensively than those with one car.⁷

With the available data, we cannot identify the individual fixed effect, ν_i . So, we cast the econometric model in terms of the *difference* in the driver's usage between consecutive service visits,

$$\Delta q_{it} = q_{it} - q_{it'} = [e^{-\theta_2 t} - e^{-\theta_2 t'}] - \beta_1 \Delta g_t - \beta_2 \Delta c_t - \frac{\lambda S_i}{\hat{Q}_i} \Delta t + \Delta \xi_{it}, \quad (18)$$

⁷Empirically, the retail price of cars rose from 2001 to 2002, and then fell until 2009, and then rose again. With lower prices, some households may have purchased a second car, and so, with two cars, would use each car relatively less, thus, giving rise to correlation between lower car prices and less usage.

where $\Delta g_t = g_t - g_{t'}$, $\Delta c_t = c_t - c_{t'}$, and $\Delta \xi_{it} = \xi_{it} - \xi_{it'}$, and where the interval between service visits, $\Delta t = t - t'$, may vary. The differencing removes all unobservable time-invariant attributes of the individual that may influence usage, and leaves $\Delta \xi_{it}$ as pure idiosyncratic error.

The essence of our empirical strategy is to 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. In the Appendix, we provide a formal justification of the identification.

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,

$$S_i = [0.25 \times ARF_i] + [0.2 \times COE_i] + \alpha P_i, \quad (19)$$

where P_i is the ex-policy price (wholesale cost, customs duty, GST, and retail mark-up) as defined in (7) and $\alpha \in [0, 1]$. This specification allows a fraction, α , of the ex-policy price to be sunk. Substituting above, the econometric model becomes

$$\Delta q_{it} = [e^{-\theta_2 t} - e^{-\theta_2 t'}] - \beta_1 \Delta g_t - \beta_2 \Delta c_t - \frac{\lambda}{\hat{Q}_i} [0.25 \times ARF_i + 0.2 \times COE_i + \alpha P_i] \Delta t + \Delta \xi_{it}, \quad (20)$$

which identifies the driver's sensitivity to sunk cost, λ , and the fraction of the ex-policy price which is sunk, α . For estimation, we assumed that the $\Delta \xi_{it}$ are normally distributed with mean, 0, and variance, σ^2 .

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 estimated 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. Gouriéroux and Montfort (1990) show that the MSL estimator is consistent and asymptotically normal as the number of draws, $M \rightarrow \infty$, and number of individuals, $N \rightarrow \infty$.⁸

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 lifetime of the car, its

⁸See Gouriéroux and Montfort (1996) for the use of simulation based models for statistical inference, and also Lerman and Manski (1981), Pakes and Pollard (1989), Gouriéroux and Montfort (1990), Hajivassiliou and Ruud (1994), and Hajivassiliou and McFadden (1998).

distribution must have positive support. Furthermore, it seemed reasonable to assume that the distribution of \hat{Q}_i is continuous. Specifically, we assumed that $\ln(\hat{Q}_i)$ follows a normal distribution with the mean corresponding to the sample average of usage, and the variance as a free parameter, estimated along with the key parameters of interest. In robustness tests, we allowed the mean of the distribution of the target usage to vary with the size of the car, and let the target usage be distributed according to gamma distribution.

Therefore, the likelihood function for each individual driver is

$$L_i(\eta) = \int \ell_i(\eta, \hat{Q}_i) \Phi(\hat{Q}_i), \quad (21)$$

where ℓ_i is a function of the vector of parameters to be estimated, $\eta = (\theta_1, \theta_2, \beta_1, \beta_2, \lambda\rho)$, and the target usage, and $\Phi(\cdot)$ is the lognormal distribution as explained above. We used MSL to evaluate the likelihood function,

$$\hat{L}_i(\eta) \approx \frac{1}{1000} \sum_{j=1}^{1000} \ell_i(\eta, \hat{Q}_{ij}), \quad (22)$$

with 1,000 independent draws of \hat{Q}_{ij} for each individual i . Specifically, we drew $\ln(\hat{Q})$ from the standard normal distribution 1,000 times, evaluated the likelihood function at each draw, and then used the average to approximate the likelihood in (22).^{9 10}

5 Data

Our primary source of data was the authorized dealer for a premium 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 were different models of the same brand. Consistent with the premium position of the brand, the popular models of engine sizes were around 2000 c.c. (cubic centimeters), which is relatively large in the Singapore context.

⁹We also estimated with 500 and 750 draws, and obtained quite similar results, which, for brevity, we do not report here.

¹⁰We have multiple observations of each car buyer, one for each service. For each service, let the error density be $f(\eta, m)$. For services $m = 1, 2, \dots, M$ records, the individual likelihood function $\ell_i = f(\eta, 1) \cdot f(\eta, 2) \dots f(\eta, M)$. We integrate out \hat{Q} from this expression.

Car owners make periodic visits to the authorized dealer for maintenance. The 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.

Consistent with our behavioral model of mental accounting, we limited the sample to new cars less than 120 months in age, which is the lifespan of a COE. Further, to exclude outliers, we further limited the sample to within 2 standard deviations of the logarithm of the average monthly usage.

Our next source of data was 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) and matching with the LTA data, we were left with records of 6,474 cars with 34,036 service visits. Owners perform maintenance at varying intervals, and, over time, owners may switch from servicing their car at the authorized dealer to less expensive third-party service facilities. Accordingly, the data constituted an unbalanced panel.

Finally, to represent the cost of gasoline, we used the Consumer Price Index of octane-98. To represent traffic congestion, we used the number of cars (published monthly) divided by the quantity of road space in kilometers (published annually).

Table 1 reports summary statistics of the data. Average monthly usage varied between 480 kilometers up to 4,370 kilometers, with a sample average of 1,652 kilometers. The retail price of the cars ranged between S\$110,000 and S\$260,600, with an average of S\$169,600, while the average ARF and COE premium were S\$46,415 and S\$21,209 respectively. So, the ARF and COE contributed to more than 40% of the retail price. The gasoline price index increased from the high 60's in late 2001 to over 120 in 2011. Over the same period, the level of congestion increased from 86 to almost 108 cars per kilometer of road.

– Table 1 here –

6 Results

Table 2 presents the estimates of the key parameters of interest, with robust standard errors.¹¹ First, as a baseline, Table 2, column (a), reports the estimate of a specification assuming that drivers behaved according to the conventionally rational model, estimated by maximum likelihood. The coefficient of the price of gasoline, β_1 , was negative but not significant. The coefficient of the unit cost of congestion, β_2 , was positive and significant. This result suggests that usage decreased with more congestion. Finally, the coefficient representing the novelty effect, i.e., the rate of attenuation of usage with age of the car, θ_2 , was positive and precisely estimated. Apparently, owners drove less as their car aged, which is consistent with the novelty effect.

– Table 2 here –

Next, Table 2, column (b), reports the estimate of the main specification, with the sunk cost specified according to the policy structure, (19), and estimated by MSL. The coefficient of the mental accounting of sunk cost, $\lambda = 0.094(\pm 0.012)$, was positive and precisely estimated. Interestingly, the coefficient of the ex-policy price, $\alpha = 0.125(\pm 0.038)$, was positive and significant. Considering that the average ex-policy price was S\$102,019, car buyers behaved as if S\$12,752 (US\$10,453) was sunk. This is comparable to the sunk cost of buying a new car in the U.S.: the average price of a new car is about US\$30,000 (FTC 2013), of which about 30% is sunk.¹²

These results suggest that car owners did mentally account for the sunk elements of the ARF and COE premium, and, in addition that, they accounted for 12.5% of the ex-policy price as sunk as well. The results are consistent with 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. Our econometric model, (18), was cast in differences, and so, did not allow us to test Propositions 2(i) and 2(ii) separately.

¹¹We computed the standard errors using the Huber sandwich estimator which is robust to heteroscedasticity in the errors. The asymptotic covariance matrix was estimated as $\hat{V} = (-A)^{-1}B(-A)^{-1}$, where $A = \mathcal{L}''(\hat{\eta})$ and $B = \sum_{i=1}^I s_i(\hat{\eta})'s_i(\hat{\eta})$, with \mathcal{L} being the log-likelihood function and s_i being the score function, for car buyers, $i = 1, \dots, I$.

¹²“[W]hen you drive your car off of the lot, it depreciates in value by quite a bit. The usual number is by around 30% ... just by driving one mile” (carsdirect.com 2013).

Comparing the estimates in Table 2, columns (a) and (b), we can infer that the drivers did *not* behave in a conventionally rational way. The coefficient of the mental accounting of sunk cost, λ , was positive and precisely estimated. Further, the estimated (mean) likelihood of the model with mental accounting was somewhat higher than that of the conventionally rational model.

To interpret the estimate of the mental accounting of sunk cost, we computed the elasticity of usage with respect to the sunk cost as being $0.563(\pm 0.072)$.¹³ 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 2010. This raised the sunk cost by $0.2 \times 22,491 = \text{S}\$4,498$. Relative to the average sunk cost, S\$28,600, this would amount to an 15.7% increase, and using our estimated elasticity, would be associated with an increase in usage by 8.8% or 147 kilometers a month.¹⁴

We believe that the effect of sunk cost might be larger than this estimate for two reasons. First, most drivers have limited discretion about commuting to work and sending the children to school. Drivers would respond to the sunk cost by varying their discretionary driving. Hence, 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 the income effects. An increase in the retail car price 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 effect of sunk cost would be biased downward.

We prefer specification (b) over the alternatives presented below – scaling the marginal benefit by a factor related to the retail price and representing the sunk cost as a proportion of the retail price – because it is simple and fits the data well. Below, we report multiple

¹³Consider an increase in the sunk cost by S\$1,000. This would increase usage over the entire life of the car, with a larger effect in the earlier months and smaller effect in the later months. By the estimated λ in Table 2(b), the total increase in usage would be 3,918 kilometers over 120 months, which amounts to an average of 32.7 kilometers a month. Dividing by the average monthly usage, 1660 kilometers, and multiplying by the average sunk cost, 28.6 (in S\$'000), we get the elasticity of 0.563. We calculated the average sunk cost as $0.25 \times ARF + 0.2 \times COE + \alpha P$, where $\alpha = 0.125$.

¹⁴Our estimates were based on the normalization $\theta_3 = 1/2$, and so, the estimated coefficients would change with the normalization. However, the counterfactual effects would remain the same as the estimated coefficients adjust accordingly.

tests of robustness to check the sensitivity of our findings to alternative specifications of sunk costs, accounting for selection, allowing for differences between smaller and larger cars, and allowing for different means for target cumulative usage distribution.

Scaled Marginal Benefit

In the main specification, we accounted for possible selection by including an individual fixed effect. But, what if selection induces differences among buyers in their marginal benefit from usage? To address this possibility, we estimate a specification that allows individuals to differ in their marginal benefit by a scale factor. Since the obvious alternative explanation of the empirical relation between usage and sunk costs is selection related to the retail price of the car, we stipulate that the scale factor increases with the retail price. So, when the retail price is higher, individual marginal benefits would be scaled up and car buyers would drive more.

Let the marginal benefit be

$$\exp(\mu P_i) \cdot B'(q_t) = \exp(\mu P_i) \cdot \{ \theta_1 + e^{-\theta_2 t} - 2\theta_3 q_t \}, \quad (23)$$

with $\mu > 0$ in place of (4). After differencing, the econometric model simplifies to

$$\begin{aligned} \Delta q_{it} &= [e^{-\theta_2 t} - e^{-\theta_2 t'}] \\ &- \frac{1}{\exp(\mu P_i)} \left\{ \beta_1 \Delta g_t + \beta_2 \Delta c_t + \frac{\lambda [0.25 \times ARF_i + 0.2 \times COE_i + \alpha P_i]}{\hat{Q}_i} \Delta t \right\} \\ &+ \Delta \xi_{it}. \end{aligned} \quad (24)$$

Table 2, column (c), reports the estimate of (24), 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, λ , was positive and precisely estimated. 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, $0.643(\pm 0.190)$, was close to that implied by the preferred estimate.

We accounted for the effect of selection on usage in three different ways – by identifying the sunk cost effect through its effect on the rate of attenuation of usage with age of the

car, by estimating a first-differenced model of usage, and by allowing the marginal benefit to increase with the retail price. Accordingly, we feel confident that our finding of the sunk cost fallacy is robust to any selection effect.

Proportionate Sunk Costs

The structure of the ARF and COE rebates is quite complex. It is possible that car buyers do not understand these intricacies, and they perceive that the sunk cost is 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,

$$S_i = \rho \cdot \text{Retail price.} \quad (25)$$

In this robustness check, the econometric model simplifies to

$$\Delta q_{it} = [e^{-\theta_2 t} - e^{-\theta_2 t'}] - \beta_1 \Delta g_t - \beta_2 \Delta c_t - \frac{\lambda \rho \cdot \text{Retail price}}{\hat{Q}_i} \Delta t + \Delta \xi_{it}. \quad (26)$$

Estimation of model (26) identifies $\lambda\rho$, and cannot separately identify λ and ρ .

Table 2, column (d), reports the estimate of (26), estimated by MSL. The estimated coefficient of $\lambda\rho$ was positive and precisely estimated. Importantly, the implied elasticity, $0.852(\pm 0.071)$, was very close to that implied by the preferred estimate. The fit of this variant was somewhat worse than the preferred estimate, with the mean likelihood being slightly lower.

Small vis-a-vis Large Cars

So far, we have estimated the average effect of sunk costs on usage over all car buyers. However, people differ in the extent to which they engage in mental accounting (Shafir and Thaler 2006). For both policy and managerial strategy, it is useful to explore such heterogeneity. One dimension of possible difference is between buyers of small vis-a-vis large cars.

Another reason to explore behavioral differences between buyers of small and large cars is a possible correlation between the novelty effect and price of the car. 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 increase with retail prices, the data would show faster attenuation of usage among the larger, more expensive cars.

To investigate, we estimated the preferred specification separately on small and large cars. The cars in our sample divided roughly equally into two segments at engine size of 2500 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.

Table 2, columns (e) and (f), report the estimates on the two segments, estimated by MSL. Contrary to the hypothesis of differential novelty effects, there was no difference in the estimated coefficient of the novelty effect, $\theta_2 = 0.003$, between small and large cars. The estimated coefficient of the effect of sunk costs among buyers of small cars, $0.074(\pm 0.011)$, was positive and very precise. By contrast, the estimated coefficient was smaller among buyers of large cars, $0.060(\pm 0.0302)$, and was also precisely estimated. The implied elasticities were close, and in fact, were not statistically different.

Apparently, buyers of small and large cars were equally sensitive to sunk costs.

Heterogeneous Distributions of Target Usage

Our preferred estimate assumed that, among all car buyers, the target cumulative usage followed the same distribution, which is a fairly standard way of dealing with the unobserved heterogeneity. The next estimate checked the robustness of our findings to this assumption. We allowed the mean target usage to vary, and specifically, drew the simulated values for cumulative target usage from a log-normal distribution, with different means for the small (below 2500 c.c.) and large (above 2500 c.c.) cars.

Table 2, column (g), reports the results, estimated by MSL. Compared to the preferred estimate, the main difference was that the estimated sunk proportion of the ex-policy price, α , was about one-third smaller. Otherwise, the estimates were quite close. In particular, the implied elasticity of usage with respect to sunk cost, $0.506(\pm 0.043)$, was similar to the

preferred estimate.

7 Implications for Public Policy and Pricing

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. Historically, the Singaporean government sought to manage traffic congestion through pricing of road usage and discouraging 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 2010, the quota of COEs in categories “B” and “E” fell by one-third from 3818 to 2569.¹⁵ The quota reduction coupled with growth of the Singapore economy resulted in the COE premium increasing sharply by S\$22,491 from S\$689 to S\$23,180. This increased the sunk cost of buying a car by $0.2 \times 22,491 = \text{S}\$4,498$. Using our preferred estimate, this increase in the sunk cost would be associated with an increase in monthly usage by 147 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 the car usage (as the government intended) by 2.07 million kilometers a month. On the other hand, based on our main estimate, the concomitant increase in the COE premium would have been associated with an increase in driving (which the government did not intend) by 0.38 million kilometers a month. So, mental accounting for sunk costs would give rise to a countervailing effect.

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

“because sunk costs matter, the high fixed cost of car ownership can be inimical to our objective of restraining car usage. Thus, instead of simply relying on

¹⁵The 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”.

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).¹⁶

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 policy makers 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 have implications for the pricing of durable industrial goods such as enterprise software and manufacturing equipment. For example, producers of enterprise software such as Oracle sell systems and then also sell complementary post-sale services to their installed base of customers. Similarly, manufacturers of equipment such as Tetrapak 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 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).

8 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 over time.

¹⁶Leong 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.

Then, we took the model to a proprietary panel data-set of 6,474 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, viz., that, among cars with larger sunk costs, usage attenuated with age of car relatively faster. We also found evidence suggesting that the effect of the sunk cost increased with the magnitude of the sunk cost relative to the price of the car. Our results were robust to alternative explanations, the specification of sunk costs, and the type of car.

Our empirical finding suggests that individuals cannot self-correct the effect of sunk costs on decision-making (or cannot fully self-correct) even in a situation of high stakes. 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 high-stakes situations. Our reason for thinking so 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 the life of the good, and that the rate of attenuation would increase with the sunk cost.

In contrast to our results, in their large-scale field experiment on the pricing of a water-purification chemical in Zambia, Ashraf et al. (2010) found no effect of sunk costs on consumer behavior. The context of our study differed from theirs in several respects. We focused on usage of a high-involvement durable that is quite expensive, so given the high stakes, consumers might pay more attention. Further, car usage is a continuing decision and not just a one-off exercise. The limitation of our study is that it was observational, being based on actual behavior in response to changes in prices due to the continuing government policy. There was no random assignment of sunk costs to different individuals. Hence, we could not absolutely rule out some unobserved factor accounting for the apparent sunk cost effect.

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)? Besides the passage

of time, what other factors amplify or diminish the effect of sunk costs on decision-making? What other factors affect an individual's ability to overcome the effect of sunk costs? Are people with training in management or economics less prone to the sunk cost fallacy?

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 Behaviour 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, “Mnemonics: 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] carsdirect.com, “New Car Depreciation Myths and Facts” [Accessed, March 22, 2013].
- [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] Federal Trade Commission (FTC), “Buyer a New Car”, <http://www.consumer.ftc.gov/articles/0209-buying-new-car> [Accessed, March 22, 2013].
- [11] 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.

- [12] Gouriéroux, Christian, and Alain Monfort, “Simulation Based Inference in Models with Heterogeneity”, *Annales d’Economie et de Statistique*, Vol. 20/21, 1991, 69-107.
- [13] Gouriéroux, Christian, and Alain Monfort, *Simulation-Based Econometric Methods*, Oxford, Oxford University Press, 1996.
- [14] Hajivassiliou, Vassilis A., and Daniel McFadden, “The Method of Simulated Scores for the Estimation of LDV Models”, *Econometrica*, Vol. 66, 1998, 863-896.
- [15] Hajivassiliou, Vassilis A., and Paul A. Ruud, “Classical Estimation Methods for LDV Models Using Simulation”, in R.F. Engle and D. L. McFadden, Eds., *Handbook of Econometrics*, Volume 4, Amsterdam, North-Holland, 1994, 2384-2441.
- [16] Hastings, Justine, and Jesse M. Shapiro, “Fungibility and Consumer Choice: Evidence from Commodity Price Shocks”, Working Paper, Chicago Booth School of Business, Revised, January 2013.
- [17] Just, David R., 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.
- [18] 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.
- [19] Lerman, Steven R., and Charles F. Manski, “On the Use of Simulated Frequencies to Approximate Choice Probabilities”, in C. F. Manski, and D. McFadden, Eds., *Structural Analysis of Discrete Data with Econometric Applications*, Cambridge, MA, MIT Press, 1981, 305-319.
- [20] Lew, Yii Der, and Wai Yan Leong, “Managing Congestion in Singapore – A Behavioural Economics Perspective”, *Journeys* (Land Transport Authority, Singapore), May 2009, 15-22.
- [21] McAfee, R. Preston, Hugo M. Mialon, and Sue H. Mialon, “Do Sunk Costs Matter?” *Economic Inquiry*, Vol. 48, No. 2, 2010, 323-36.

- [22] 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.
- [23] Pakes, Ariel S., and David Pollard, “Simulation and the Asymptotics of Optimization Estimators”, *Econometrica*, Vol. 57, No. 5, 1989, 1027-1057.
- [24] 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.
- [25] Png, Ivan, *Managerial Economics*, 4th edition, Abingdon, UK: Routledge, 2012.
- [26] Shafir, E. and Thaler, R. H. “Invest now, drink later, spend never: On the mental accounting of delayed consumption”, *Journal of Economic Psychology*, Vol. 27, 2006, 694-712.
- [27] 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.
- [28] 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.
- [29] 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.
- [30] Thaler, Richard, “Towards a Positive Theory of Consumer Choice”, *Journal of Economic Behavior and Organization*, Vol. 1 No. 1, March 1980, 39-60.
- [31] Thaler, Richard, “Saving, fungibility and mental accounts”, *Journal of Economic Perspectives*, Vol. 4, 1990, 193-205.
- [32] Thaler, Richard, “Mental Accounting Matters”, *Journal of Behavioral Decision Making*, Vol. 12 No. 3, September 1999, 183-206.

Appendix

Generalizing (13), 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,

$$\frac{dq_t^*}{dR} = \frac{\partial q_t^*}{\partial R}(t, c_t, g_t, R, S) + \frac{\partial q_t^*}{\partial S}(t, c_t, g_t, R, S) \cdot \frac{dS}{dR}. \quad (27)$$

In (27), the partial derivative of usage with respect to the retail price, $\partial q_t^*/\partial R$, represents the selection effect, i.e., that drivers who drive more are willing to pay a higher price for the car. The partial derivative of usage with respect to the sunk cost, $\partial q_t^*/\partial S$, represents the sunk cost effect.

By studying the variation of usage with the retail price, (27), we cannot distinguish the selection effect from the sunk cost effect. To distinguish the two effects and identify the sunk cost effect, we study the variation of usage with retail price and time. Differentiating (27) with respect to time,

$$\frac{d^2 q_t^*}{dRdt} = \frac{\partial^2 q_t^*}{\partial R \partial t}(t, c_t, g_t, R, S) + \frac{\partial^2 q_t^*}{\partial S \partial t}(t, c_t, g_t, R, S) \cdot \frac{dS}{dR} + \frac{\partial q_t^*}{\partial S}(t, c_t, g_t, R, S) \cdot \frac{d^2 S}{dRdt}. \quad (28)$$

Our central identifying assumption is that the propensity for higher usage among drivers who pay higher retail prices does not change with the age of the car, i.e., $\partial^2 q_t^*/\partial R \partial t = 0$. Since the retail price and sunk cost do not change with the age of the car, $d^2 S/dRdt = 0$. Substituting in (28)

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

From the data, we can estimate the left hand side of (29), and then integrate over t to obtain

$$\frac{\partial q_t^*}{\partial S}(t, c_t, g_t, R, S) \cdot \frac{dS}{dR}. \quad (30)$$

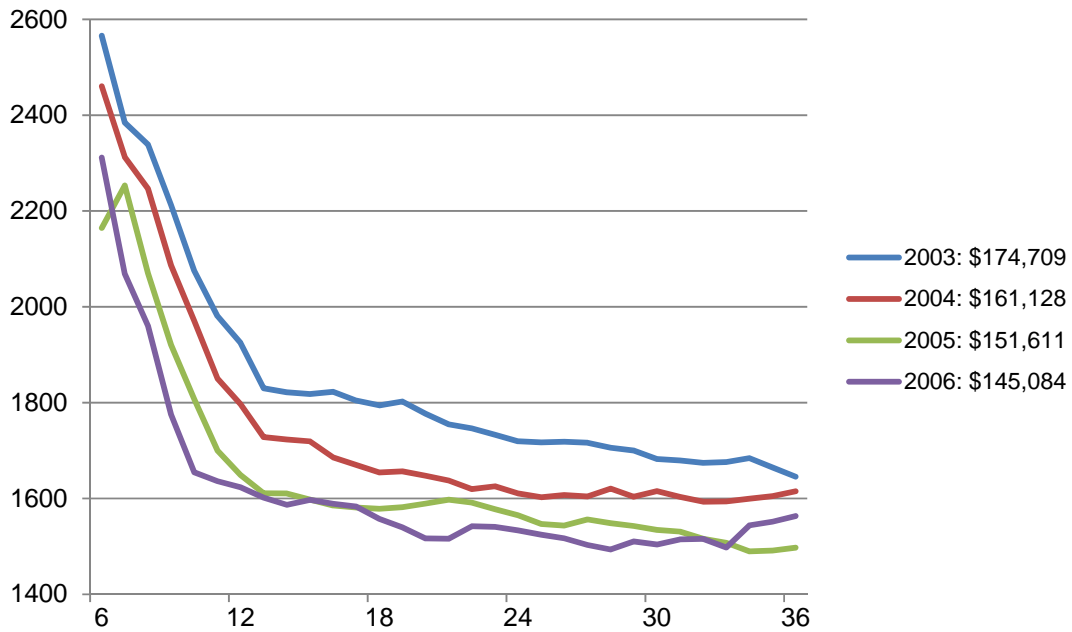
Then, the parameter, $\partial q_t^*/\partial S$, characterizes the sunk cost effect.

Figure 1. Retail car price and monthly usage



Note: Average retail price of cars (in \$'000) on left-hand axis, and average monthly usage over life of car (in kilometers) on right-hand axis. Data for the two most popular models in the sample.

Figure 2. Average monthly usage over life of car



Note: Data for Model A, the most popular in the sample.

Figure 3. COE and ARF rebate structure

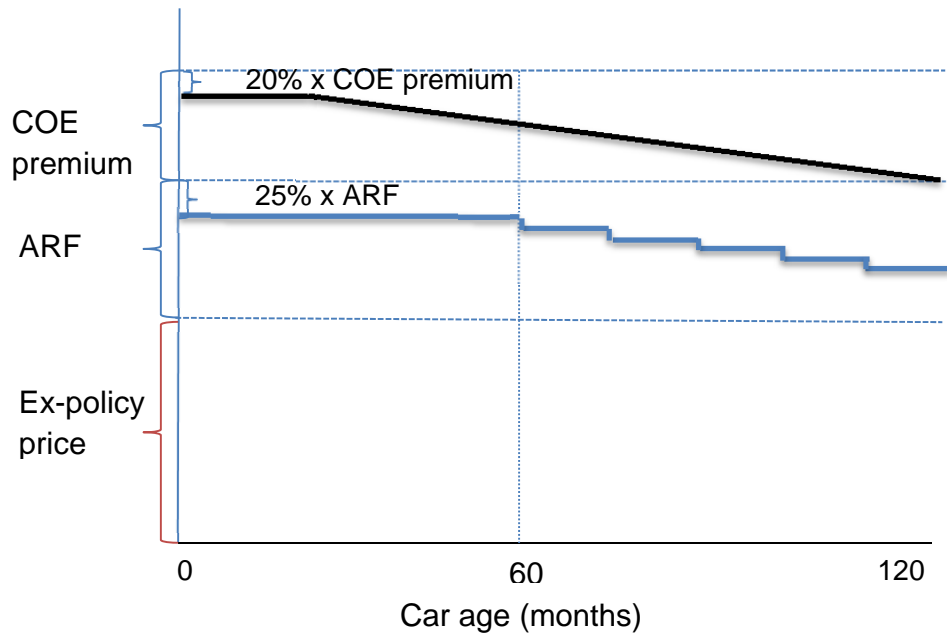
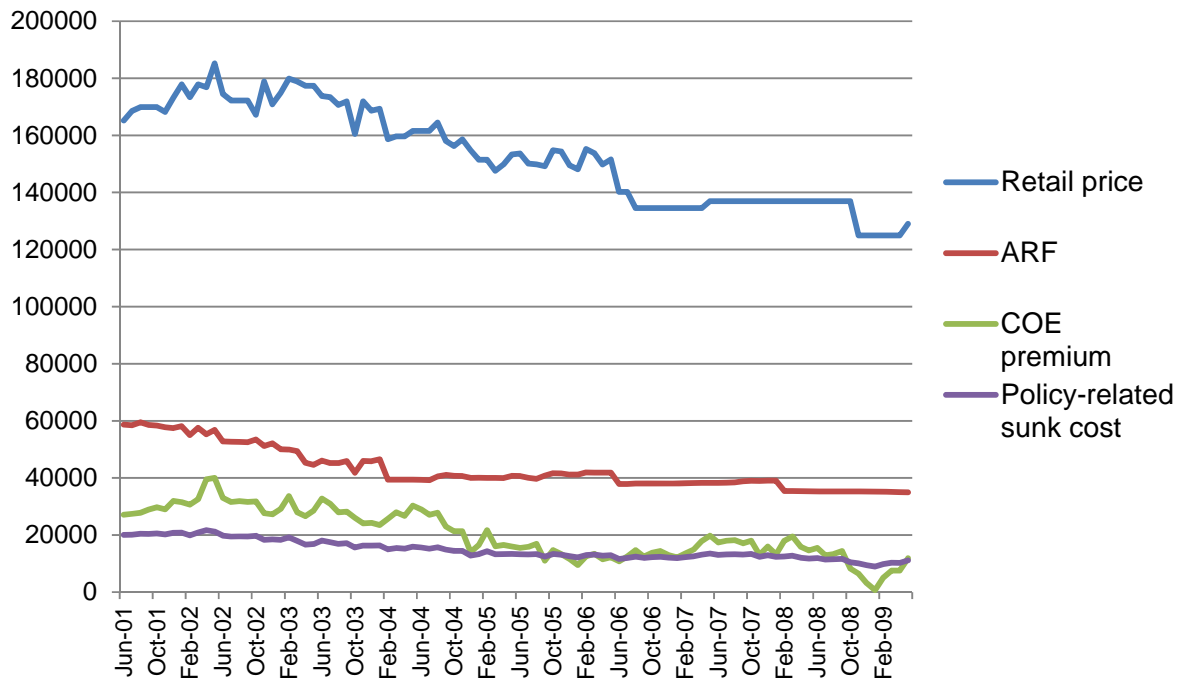


Figure 4. Price and costs



Notes: Data for Model A, the most popular in the sample; price and costs in \$.

Figure 5. Effect of mental accounting for sunk cost

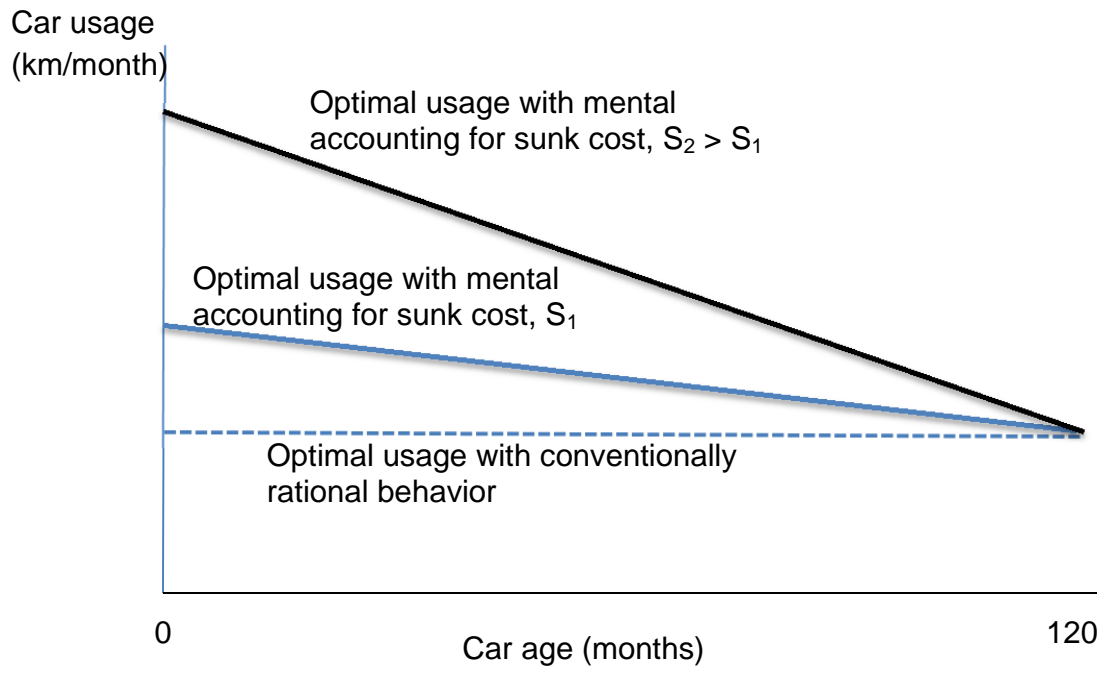


Table 1. Summary statistics

Variable	Unit	Mean	Standard deviation	Min	Max
Usage	'000 kilometers per month	1.660	0.68	0.48	4.37
Retail price	S\$'000	169.6	27.2	110.0	260.6
ARF	S\$'000	46.4	8.5	31.0	73.0
COE premium	S\$'000	21.2	8.9	0.7	68.5
Gasoline price	2006 January = 100	94.80	16.30	69.10	126.60
Congestion	Cars per kilometer	95.30	8.20	85.80	107.60

Note: US\$1 = S\$1.22

Table2. Effect of sunk cost on usage

Variable	(a) Convent- ional rationality	(b) Mental accounting for sunk cost	(c) Scaled marginal benefit	(d) Sunk cost proportional to retail price	(e) Smaller cars	(f) Larger cars	(g) Hetero- geneous target usage
Gasoline cost, β_1	-0.0001 (0.000)	-0.0003 (0.000)	-0.0006* (0.000)	-0.0003 (0.000)	-0.0006* (0.000)	-0.0001 (0.000)	-0.0003 (0.000)
Congestion cost, β_2	0.027*** (0.002)	0.010*** (0.002)	0.009** (0.003)	0.010*** (0.002)	0.011*** (0.003)	0.003 (0.003)	0.011*** (0.002)
Age, θ_2	0.010*** (0.000)	0.004*** (0.000)	0.000 (0.000)	0.005*** (0.000)	0.003** (0.001)	0.003** (0.001)	0.004*** (0.001)
Sunk cost, λ		0.094*** (0.012)	0.237*** (0.031)		0.074*** (0.011)	0.060** (0.022)	0.095*** (0.008)
Sunk cost part of ex-policy price, α		0.125*** (0.038)	0.208*** (0.039)		0.233*** (0.080)	0.326* (0.186)	0.094*** (0.023)
Sunk cost, $\lambda\rho$				0.024*** (0.002)			
No. of observations	6474	6474	6474	6474	3581	2893	6474
Mean log likelihood	-2.772	-2.752	-2.748	-2.755	-2.693	-2.819	-2.752
Log likelihood	-17946.2	-17815.1	-17788.7	-17833.8	-9643.3	-8155.7	-17819.2
Elasticity	n.a.	0.563*** (0.072)	0.643*** (0.190)	0.852*** (0.071)	0.534*** (0.079)	0.734*** (0.269)	0.506*** (0.043)

Notes: Estimated by simulated maximum likelihood regression, with lognormal distribution of target usage, except for column (a); Dependent variable is first difference of usage ('000 km per month). Column (a): Conventionally rational behavior; Column (b): With mental accounting for sunk costs and sunk cost according to COE and ARF rebate policy (preferred estimate); Column (c): Marginal benefit inflated by scale factor depending on retail price; Column (d): Sunk cost represented by proportion of retail price; Column (e): Sub-sample of buyers of small cars; Column (f): Sub-sample of buyers of large cars; Column (g): With separate distributions of target usage for buyers of small and large cars. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).