Intertemporal Preferences and the Adoption Decision for Bluetooth Speakers

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Abstract

The adoption decision for durable goods is intertemporal by definition. However, estimating utility and discount functions from revealed preference data using discrete choice models is difficult because of an inherent identification problem. To overcome this issue, we use stated preference data. Specifically, we employ the experimental design of Dubé, Hitsch, and Jindal (2014), where future prices are known and that elicits intertemporal adoption decisions for Bluetooth speakers in a discrete choice framework. We find considerably lower discount factors than typical market interest rates would suggest. The values are also smaller than respondents' matching-based discount factors, even though the correlation is positive and significant. Furthermore, there are substantial differences in discounting across respondents (i.e., heterogeneity in time-preferences).

Keywords: intertemporal preferences, durable goods adoption

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Introduction

Understanding the adoption decision for a durable good is of great importance in consumer behavior, quantitative marketing, and economics (Nair, 2007; Gowrisankaran and Ryzman, 2012; Melnikov, 2013). Adopting a new product is a dynamic decision problem because deciding if and when to adopt depends on (static) preferences for the product, the discounted future utility flow, and expectations about future market conditions. Dynamic discrete choice models are well suited for studying such adoption decisions, but they suffer from a fundamental identification problem if estimated from market (i.e., revealed preference) data (Magnac and Thesmar, 2002), where utility functions, discount factors, and subjective beliefs about future market conditions are (typically) not jointly identified. As a simple solution, researchers often fix the discount factor in the estimation at a "reasonable value" (Gowrisankaran and Ryzman, 2012). Recently, Dubé, Hitsch, and Jindal (2014; henceforth DHJ) presented a new approach for jointly estimating discount and utility functions from stated choice data. The authors propose a novel design for a discrete choice experiment, where future prices of products are given (i.e., no uncertainty about future market conditions). In several choice scenarios, respondents state (given current and future prices) if they would adopt a new durable good and, if so, when and which particular alternative they would choose. This information enables the joint identification of discount and utility functions.

We apply the approach of DHJ and analyze the adoption decisions for portable Bluetooth speakers over the next three years. We test whether consumers are forward-looking and, if so, how they value the future. Given limited empirical results on intertemporal preferences in the context of durable good adoption decisions, our effort here can be viewed as a conceptual replication of DHJ. Furthermore, we also measure discount factors using matching-tasks, where the same respondents were told to imagine that they had won money and could get it now or later, and they had to state how much (more) money they would like to receive to wait for one, two, or three years (Thaler, 1981). This enables us to study differences in discount factors across methods (and respondents) to improve further our understanding of the novel approach proposed by DHJ to elicit intertemporal preferences.

Choice Model-Based Discount Factors

The model in our analysis captures the inherently dynamic choice problem that consumers face when making adoption decisions for durable goods. That is, consumers interested in the product category have to decide whether they want to adopt the product now or later. Adopting now has immediate benefits (i.e., being able to use the product), but waiting might be beneficial if prices will be lower in the future, which is a reasonable assumption for many durable goods categories (e.g., consumer electronics).

Assuming price predictions for all brands $j=1,\ldots,J$ to be known to all decision makers (i.e., respondents) $i=1,\ldots,I$ simplifies the problem considerably (see DHJ for more details): For each choice task $c=1,\ldots,C$, respondent i can either state that she adopts brand j in period $t\leq T$ ($y_i=(j,t)$), or not ($y_i=0$).

We start with a simple linear additive utility function:

$$u_{ijt}=\gamma_{ij}+\kappa_i\cdot price_{jt},$$

where γ_{ij} are intercepts for each brand j and κ is the price coefficient. All parameters are respondent-specific. The value in $t=0$ from adopting the brand j in t is:

$$\omega_{ijt}=f_i(t)\cdot(\gamma_{ij}+\kappa_i\cdot price_{jt}).$$

We use a discrete choice model assuming geometric discounting (Samuelson, 1937): $f_i^G(t)=\delta_i^t$. In this model the instantaneous discount rate, which is defined as $-f'_i(t)/f_i(t)$, is $-\log(\delta)$ and hence constant. The discount function $f_i(t)$ maps the net utility u_{ijt} from the adoption decision at time t to the time when the choice experiment takes place ($t=0$). Adding an i.i.d. type I extreme value distributed error term ϵ_{ijt} to ω_{ijt} leads to a simple multinomial logit model with $J \cdot T+1$ alternatives, where the probability of adopting brand j in t is:

$$Pr(y_i=(j,t) \vee price_{jt}, \theta_i)=\frac{\exp(\omega_{ijt})}{1+\sum_{t'}^{T}\sum_{j'}^{J}\exp(\omega_{it'j'})}.$$

with $\theta_i=[\gamma_{i1},\ldots,\gamma_{iJ},\kappa_i,\delta_i]' \sim MVN(\bar{\theta},\Sigma)$.

To elicit the intertemporal preferences, we show each respondent multiple choices for several price scenarios (i.e., choice tasks), leading to a panel structure of the data. In each scenario, the respondent has to choose if and when she wants to adopt a specific brand. DHJ show that the variation in current and future market conditions is sufficient to jointly identify of the discounting and utility functions. We estimate the model using maximum simulated likelihood (Train, 2009).

Matching-Based Discount Factors

We also considered a second method for the elicitation of discount factors (see Frederick et al., 2002 for an overview). In particular, we used matching tasks where respondents were told to imagine they had won 200 Euros in a lottery and could take the money now or wait for one, two, or three years and receive a larger amount (Thaler, 1981). The respondents were then asked to equate each intertemporal option:

- €200 now = €_____ in 1 year
- €200 now = €_____ in 2 years
- €200 now = €_____ in 3 years

The monetary value and the time frame match our setup for the adoption choice of Bluetooth speakers. However, while the adoption tasks in the choice experiment provide a relevant context and appear to be more realistic, an advantage of matching tasks is that they allow calculating model-free estimates of discount factors for each respondent and period (Urminsky and Zauberman, 2016). The respondent- and period-specific discount factors follow from $\delta_{it}=200/v_{it}$, where v_{it} is the monetary value that respondent i wants for waiting t years instead of taking the 200 Euros now. We further compute respondent-specific estimates for the discount factors using the geometric mean: $\hat{\delta}_i=\sqrt[3]{\delta_{i1}\cdot\sqrt{\delta_{i2}}\cdot\sqrt[3]{\delta_{i3}}}$.

Empirical Setup and Data Description

We created an online survey that included the experimental price variation looking at adoption decisions of portable Bluetooth speakers. At the time of the data collection (June 2017), this product category was reasonably new, but already popular, in particular, with younger consumers. We included the two most prominent brands, UE (Megaboom) and JBL (Charge 2+), and explained to the respondents that the prices are predictions of experts that they should interpret as given (i.e., without uncertainty). In line with the real market (at that time), the prices of UE are higher than the prices of JBL. Furthermore, as usual for consumer electronics, all future prices are decreasing, providing an incentive to delay the adoption decision. Lastly, we included the next three years as future periods and explained to the respondents that opting for

the outside-good means that they will not adopt any of the brands in the product category, also not in $T>3$.

We collected data online and distributed a link to marketing students at a major European University. Each respondent in our sample was asked to make $C=18$ adoption decisions, provided the relevant information for the matching-based discount factors, and answered several additional questions about product class experience, socio-demographics, as well as scales related to the cognitive process during decision-making. 312 respondents completed all choice tasks. We further cleaned the data (e.g., straight-lining, unreasonable fast answering, no category interest), resulting in a final data set with 244 respondents and 4392 adoption choices. Of these respondents, 70.1% are females, 77.1% are 30 years old or younger, 93.5% are (bachelor or master) students, and 62.7% have an income of less than 1500€. Our convenience sample consists, therefore, mainly of younger people, that are well educated and have only a limited budget.

A descriptive analysis reveals that the majority of the respondents switches between brands and times for adoption. The share for not adopting is 8.8%. Furthermore, more than 80% of the respondents' decisions are consistent with forward-looking behavior. In sum, the data appears to be well suited for the choice model presented above.

Comparison of Discount Factors

We now discuss the estimated discount factors at the individual level and compare the two approaches. For the discrete choice model, the empirical distribution of $\overset{¿}{\delta}_i$ shows almost full support between 0 and 1 (the range is $[0.05, 0.9]$), with a concentration around 0.4. Indeed, the mean of the individual values is 0.43, and the standard deviation is 0.21. Thus, we find rather low discount factors (even for the yearly time-intervals in our study) and a large amount of heterogeneity. Thus, our application replicates the general results of DHJ.

The results for the matching-based discount factors yield mean aggregate estimates of $\bar{\delta}_1=0.72$, $\bar{\delta}_2=0.56$, and $\bar{\delta}_3=0.45$. These values look like geometric discounting would also be a reasonable model for discount factors from matching tasks and thus we compute respondent-specific values as explained above. The values are also very heterogeneous, but the distribution of $\overset{¿}{\delta}_i$ is now more skewed towards the upper bound, with a mean of 0.73 and a range of [0.25,0.99]. These results are very similar to findings reported in the literature (Frederick et al., 2002).

Next, we want to compare the results from both methods (i.e., choice model vs. matching tasks). While the distributions for the discount factors somewhat differ, both methods still might lead to similar insights at the respondent-level if discount factors across both methods (but within respondents) are correlated.

Before computing and testing the Pearson correlation, we logit-transform the discount factors: $\overset{¿}{\lambda}_{ik}=\ln(\overset{¿}{\delta}_{ik}/(1-\overset{¿}{\delta}_{ik}))$, with $k \in \{C, M\}$ indicating the two methods. Correlating δ instead of λ could bias the result towards zero because δ is bounded between 0 and 1. Furthermore, also the potentially large measurement errors of the discount factors at the individual-level can lead to an attenuation of the correlation.[4] To deal with this issue we employed the correction method of

4 We computed standard errors for the discount factors using the conditional variance in case of the choice model (see Greene 2012, p. 644) and the "simple formula" (Harding et al. 2014) in the case of matching. We used the delta method to obtain standard errors for λ.

Spearman (1904), where the corrected correlation is $\rho = \frac{corr\left(\hat{\lambda}_C, \hat{\lambda}_M\right)}{\sqrt{\left(R_{\lambda_C} \cdot R_{\lambda_M}\right)}}$. Here the numerator is the Pearson correlation without correction and R_{λ_k} is the reliability coefficient of λ_k. We used the average of the standard errors in both methods to compute these reliability coefficients.

[Insert Figure 1 about here]

Figure 1 (panel a) shows the scatterplot between the transformed discount factors of both methods. We see a positive but rather weak relationship between both methods ($\rho \approx 0.195$). Nevertheless, the value is significant (95% CI [0.053, 0.330]) and hence the results from the choice model are validated using a different, established method. Panel b of figure 1 shows a Bland-Altman plot, where the differences in $\Delta_\lambda = \hat{\lambda}_C - \hat{\lambda}_M$ are plotted against $\frac{\hat{\lambda}_C + \hat{\lambda}_M}{2}$. A correlation does not necessarily imply an agreement between measures and the graph again shows, that matching-based discount factors are larger on average (i.e., $\Delta_\lambda < 0$). However, the graph further clarifies that this difference is not affected by the average values; thus, the level of (dis-) agreement is stable.

To explore potential relationships between the level of discounting and observed heterogeneity of the respondents, we regress $\hat{\lambda}_C$ and $\hat{\lambda}_M$ on demographic variables, the survey duration, and the score of the cognitive reflection test (we used the 5-item version proposed by Böckenholt, 2012). We fitted the linear models using WLS with the inverse of the squared standard errors of the λ_{ik} values as weights.

[Insert Table 1 about here]

Table 1 summarizes the regression results with several interesting differences between the discount factors obtained from both methods. In the choice model, higher income is associated with a lower level of patience, which makes intuitive sense. Most other variables, in particular, the ones that might serve as an indicator for more deliberate and rational decision-making, do not affect the discount factors. Interestingly, respondents with longer survey durations have lower discount factors, which indicates that low(er) discount factors are not necessarily a result of low attention during the choice experiment. Matching-based discount factors, on the other hand, are indeed positively affected by higher scores of the cognitive reflection test, as in Frederick (2005), or a higher level of education. These respondents might interpret this elicitation method as a test, and try to give answers that imply more "reasonable" discount factors. As before, longer survey durations are also related to lower discount factors. For matching-based discount factors, income has no significant effect. In both cases, the R^2-values of about 0.11 and 0.12 indicate that the variables explain only some variance in the (transformed) discount factors.

Conclusion

Our results show that consumers are forward-looking: both the dynamic model as well as the model-free within-subject analysis provide evidence for forward-looking behavior. The discount factors are considerably lower than typical market interest rates would imply (≈ 0.43), and we do not find compelling evidence for hyperbolic discounting (based on the adoption choices). These results are in agreement with the findings from DHJ. We find that the discount factors obtained from matching tasks (for the same respondents) are considerably higher (≈ 0.73). The correlation of discount factors between both methods is positive and significant, but the magnitude is

relatively small. Regression analyses reveal that different variables are related to discount factors in both methods. Higher income negatively affects discount factors in adoption choices, whereas a higher level of education or higher scores in the cognitive reflection test only positively affect matching-based discount factors. This explains to some degree why the correlation between discount factors between both methods is not higher.

The study faces several limitations that need to be addressed in future research. We do not use incentive alignment in our experiment, which could affect people's discount factors. In a follow-up study, we plan to address this issue by conducting an incentive aligned experiment with a more representative sample, including also a new product category. Although, the approach by Dubé et al. (2014) is a rather artificial construct, it allows us to gain valuable insights on intertemporal preferences of consumers for marketers (e.g., for new product introduction and pricing).

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Figure 1: Comparison of Individual Discount Factors

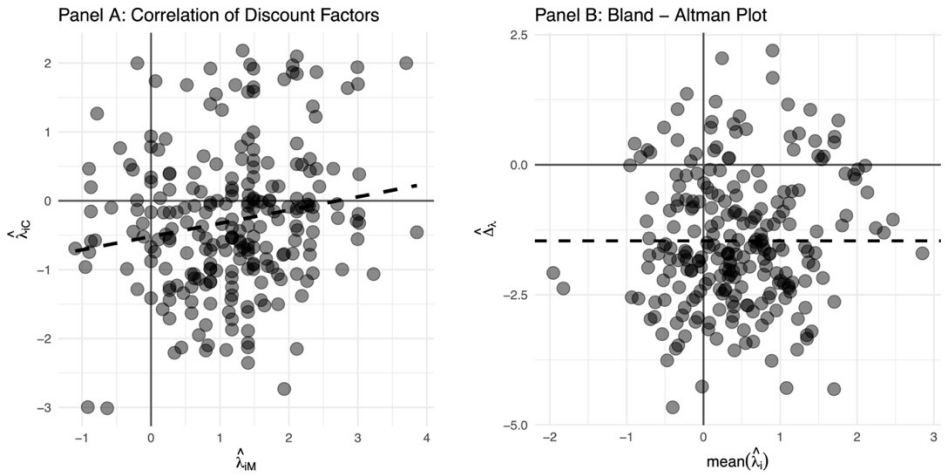

Table 1: Drivers of discount factors

	Dependent Variable:			
	$\hat{\lambda}_C$		$\hat{\lambda}_M$	
Intercept	0.930*	(0.329)	1.616*	(0.267)
income (>1000 Euro)	-0.445*	(0.128)	0.164	(0.134)
gender (male)	-0.132	(0.135)	0.197	(0.132)
age (26 and older)	0.134	(0.132)	−0.381*	(0.143)
edu (BSc or higher)	-0.121	(0.110)	0.420*	(0.136)
log(duration)	-0.240*	(0.098)	−0.183*	(0.071)
CRT score	0.008	(0.047)	0.100*	(0.050)
R^2	0.118		0.114	

Note: WLS estimates and standard errors in parentheses; * p < 0.05