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An Empirical Analysis for a Case-based Decision to Watch Japanese TV dramas

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This article empirically analyzes consumer behavior of watching TV dramas via case-based decision theory. This theory models consumer decision under uncertainty in product quality, based on subjective evaluations of previous purchases for similar goods. Our empirical analysis is concerned with *getsuku*, the Japanese TV dramas broadcasted at 9pm Monday by the Fuji Television Network, whose quality necessarily has uncertainty because no program is completely equivalent to any other. Owing to the regularity of the schedule and the long-sustained popularity of the program that enables us to be able to collect consumer data easily, we conduct a web survey of individual audiences on subjective evaluations of previously watched dramas. Our empirical analysis demonstrates better performance by the case-based models regarding both statistical model selection and one-step-ahead prediction than traditional utility-based models. We also reveal that the good performance of the case-based model in our analysis depends on the availability of individual subjective evaluations and that it is difficult to replace the individual-specific information by demographic information and aggregate data.

Keywords: Case-based decision models; Cultural Economics; TV audience rate; Getsuku; Web survey
JEL classification codes: D12; D83; Z11

1 Introduction

This article empirically analyzes TV watching behavior via a new economic model of case-based decision making. There has been an active research thread producing new

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microeconomic theories regarding consumer behavior that extend the scope of the traditional expected utility theory. However, the validity of most of the corresponding models has not been checked from an empirical perspective. The present study tries to fill the gap between theoretical and empirical studies for the case-based model.

Conventional utility-based models assume the latent expected utility from purchasing a good to be known to consumers. In addition, there are some goods whose quality is not observed by consumers before actual purchase. Under such circumstances, consumers need to adopt a different method of decision making in order to overcome the uncertainty. Case-based decision theory provides a model in which consumers predict the quality of a good from their past experiences of purchasing similar goods.

Gilboa and Schmeidler (2001) provided a unified treatment for a class of case-based models through an axiomatic approach. Gilboa et al. (2006) presented the "empirical similarity" model, which is convenient for empirical studies and satisfies the axioms of consumer decision. Lieberman (2010) and Gilboa et al. (2011) investigated econometric properties of the empirical similarity model.

Gayer et al. (2007) applied the empirical similarity model to apartment sale prices and rents using real data. In their article, they directly applied a case-based model to analyze prices without considering the equilibrium process of price setting. Nevertheless, the case-based model achieved better performance of both statistical model selection and prediction for rent than the ordinary regression model. This finding demonstrates the potential efficiency of the case-based approach in empirical research. On the other hand, our study directly analyzes consumer decision making and has a natural interpretation for empirical results.

Our empirical analysis is concerned with the consumer behavior of watching TV dramas. Cultural goods such as TV dramas have essential uncertainty in their quality because no good is completely equivalent to any other. Under utility-based models where consumers know product quality, a program with high quality must attract wide popularity. In reality, however, there are many programs that are acclaimed by critics but do not find commercial success. The case-based model can provide a natural explanation for why, even when a program has high quality, consumers do not try it unless it has similarities to previously watched programs which they regard favorably.

We concentrate on Japanese TV dramas that were broadcast at 9pm Monday by the Fuji Television Network, often called *getsuku* (short for "9pm Monday" in Japanese). In its long history from the late 1980s, the getsuku dramas have received high audience rates of from 10 to 35% and become the best-known youth-oriented dramas in Japan. Because of the regularity of its schedule and long-sustained popularity, it is easier to collect consumer data for the watching of getsuku dramas than for most other cultural goods. Therefore, we conducted a web survey to collect consumer data on past behavior and subjective evaluations for watched dramas, as well as characteristics of individual viewers. As a result, we obtained a panel dataset which records individual watching behavior for multiple dramas.

As a resource for econometric analysis, web surveys have a potential weakness in the form of sample selection, as summarized by Bethlehem (2010). Although our study is also exposed to the risk of sample selection, we have three responses to such a potential criticism. First, we know of no natural reason why those who make a case-based decision should be more or less likely to participate in web surveys. Thus, sample selection, if any exists, does not interfere with our main research topic, which is empirical validation of the case-based model. Second, watching behavior of TV dramas might be a topic that is less affected by sample selection than other topics of economic study. This is because watching TV and internet surfing share the property of being indoor leisure activities. Also, the coverage of internet access in Japan had reached 79.1% in 2011(Japan Ministry of Public Management, Home Affairs, Posts and Telecommunications, 2012). Therefore, the coverage of potential web survey participants is likely to overlap the potential drama audiences. Third, it is difficult to obtain unbiased survey data that contain individual subjective evaluations for past TV programs. Under the data availability problem, a web survey is perhaps the best practical resource for marketing-oriented research. Therefore, our analysis can provide useful insight for practical situations.

In our econometric analysis for a case-based model, we do not utilize the empirical similarity model, but rather construct a simple linear probit-type model for watching behavior. To obtain detailed properties of the model in empirical situations, we construct two specifications for the case-based model: with and without demographic information. To validate the performance of the case-based model, we also employ probit estimation for a conventional utility model in which only individual characteristics and drama characteristics are included as explanatory variables, following a study of American TV networks by Shachar and Emerson (2000). We compare performance of models regarding statistical model selection and one-step-ahead prediction for watching behavior.

We further present a method for out-of-sample type prediction analysis. As summarized in Danaher et al. (2011), advertisement on TV is highly affected by audience rate of programs. Therefore, out-of-sample prediction for watching behavior among the general population is, if possible, of practical importance. However, out-of-sample prediction based on the case-based model requires individual subjective evaluations for the prediction sample, which are burdensome to collect. As a feasible approach for prediction, we propose a method that utilizes only average subjective evaluations among those who share demographic characteristics.

Our empirical analysis yields the following results. Based on statistical model selection and one-step-ahead prediction, the case-based model clearly outperforms the traditional utility-based model. For the case-based model, specifications with and without demographic characteristics work similarly in both model selection and one-step-ahead prediction. This result shows that the case-based model works well even without consumer characteristics other than individual subjective evaluations. Furthermore, the out-of-sample type prediction shows poor performance, which implies that the aggregate information cannot replace the individual subjective evaluations in the case-based model.

Our simple linear probit model can adopt flexible extensions for empirical applications on general consumer behavior. As examples of important extensions, we introduce the premium for recently watched dramas and effects of the published audience rate to analyze peer effects. These extensions improve the performance of estimation, although these additional elements are not theoretically guaranteed to satisfy the axioms of consumer decision. This finding suggests which directions are preferable for future theoretical research studies.

With respect to the literature related to our present research, there are both theoretical and empirical studies that address the relationship between current and previous decisions. In economic theory, the rational addiction model of Becker and Murphy (1988), in which utility can be changed by accumulation of purchase experiences, can be applied to situations similar to those of our case-based models. A learning-by-consuming model, which was used by Lévy-Garbova and Montmarquette (1996) in analysis regarding theatrical performances in France using subjective evaluations, has a motivation similar to that of the case-based model. We can say that the case-based model is a way to give a micro-foundation explicitly to the learning-by-consuming behavior model. Brito and Barros (2005) and Seaman (2006) provide more discussion of the theoretical issues and related empirical methodologies in the context of cultural economics.

For empirical studies, interdependence occurring among the decision history has been investigated in state-dependent models. The state-dependent model states that consumers tend to purchase the same good repeatedly. Moshkin and Shachar (2002) and Kinjo and Ebina (2014) applied such a model to an empirical analysis of TV watching behavior. From an empirical perspective, the case-based model is more general than an ordinary state-dependent model, because the case-based model adopts not only previous purchase behavior, but also subjective evaluations for the previous purchases. This enables us to model the negative impact of unfavorable experiences, which is beyond the scope of the ordinary state-dependent models.

The organization of the remainder of this article is as follows. In Section 2, we provide a detailed description of the data. Section 3 presents our econometric framework, and the empirical findings are shown in Section 4. Section 5 concludes the article.

2 Data

We need two kinds of data for the empirical analysis of our case-based model. The first is the characteristics of the dramas, and the second is the characteristics of individual consumers. This section firstly describes the drama characteristics with a brief explanation of getsuku dramas. We then proceed to describing the consumer characteristics. We also report the design of our web survey.

2.1 Characteristics of getsuku dramas

A getsuku drama is broadcasted by the Fuji Television Network from 21:00 to 21:54 every Monday for three months. The program started in the late 1980s. Since several successful dramas in the early 1990s, such as Tokyo Love Story and The 101st Marriage Proposal (*101-kai me no puropozu*), the program has become the most popular youth-oriented series of dramas in Japan. The getsuku dramas have a large influence on popular culture, not only in Japan but also in Asian counties generally, as discussed in Iwabuchi (2004).

Although a person's lifetime watching experience is referred to in case-based decision making, it is quite burdensome to collect such retrospective information in empirical studies. Therefore, we limit our attention to only $T = 54$ getsuku drama series from January 2000 to April 2013.

To define the similarities between dramas in the case-based model, we adopt the following $K = 6$ drama characteristics and designate $\mathbf{x}^P$ as the vector of the associated variables. The first category of characteristics is the themes of the drama. As candidate themes, we consider the three themes comedy, love story, and mystery, denoted **Comedy**, **Love**, and **Mystery**, where multiple themes are allowed for each drama. Because there is no official categorization of themes, we subjectively determine the themes of the dramas based on the information on the drama homepage. The second category concerns the type of original work developed for the drama. This category of variables might represent the synergy effects of multiple media. Specifically, we introduce a novel origin dummy (**Novel**)[1].

The third category of drama characteristics is the cast, whose large influence on TV watching behavior was shown in Shachar and Emerson (2000). To consider cast effects, we firstly determined the three main characters of the drama based on its homepage. We then consider whether these characters are performed by influential actors. We investigate effects of cast for two categories. The first category is actors who are managed by Johnny & Associates, *Johnny's Jimusho* in Japanese and denoted by **Johnny's**. The second category is the specific actor Takuya Kimura, denoted using his nickname **Kimutaku**. Johnny & Associates is an acclaimed management agency for groups of young male pop singers. Many members of these groups are also popular as actors and are often cast in getsuku. Takuya Kimura is a famous actor who was cast seven times for getsuku dramas during the period of our research. Takuya Kimuya is also managed by Johnny & Associates as a member of the best-known male group in Japan, SMAP, but we eliminate him in the construction of the **Johnny's** dummy. Further, we do not adopt a cast variable that includes actresses, because there were no actresses who appeared in more than three getsuku dramas as a main character during our research period.

In the section 4.3 for extended models, we introduce the published audience rate for dramas as an additional explanatory variable. The regular audience rate of all TV programs is only researched and published by Video Research Ltd. in Japan[2]. Video Research conducts a household sample survey by minute, but we utilize the overall average during the broadcasting time of getsuku.

To explain the potential advantage of case-based modeling, we will present a brief history of the mystery theme in getsuku. Since the 1980s, getsuku had been popular for several successful love stories, whereas mystery was such a minor theme that there

[1] Another candidate origin is comics (*manga*), which are popular in Japan, but there are only three getsuku dramas based on comics during the period of our research. Thus, we do not utilize this as drama characteristics.

[2] The Japanese national TV network Nihon Housou Kyoukai also researches audience rates, but it covers only five weeks a year. The Nielsen Company once operated in Japan before the launch of Video Research, but withdrew from Japan in 2000. Fujihira (2007) presented more details about audience rate in Japan.

had been only three dramas produced from 2000 to the third quarter of 2007. In the fourth quarter of 2007, *Galileo*, however, a mystery drama based on short stories by Keigo Higashino[3] was produced. This drama obtained a high audience rate, above 20%, which is better than the preceding eight dramas. After the success of *Galileo*, there have been six mystery dramas produced from 2008 to the second quarter of 2013. This may imply that TV producers take in account audiences' previous watching behavior, which is ignored in a conventional utility-based model.

2.2 Individual characteristics

We conducted a web survey of individual viewers through Macromill Inc., on August 22nd and 23rd, 2013. The population of their monitor pool consisted of 1,147,370 individuals on August 1st, 2013[4]. From this population, we utilize a stratified sampling for gender and age by ten-year group on the basis of the 2010 Census. We restrict our sample to individuals who live alone in order to remove peer effects from family members, which was analyzed by Yang et al. (2006). We also restrict our sample to only those who are 20 to 69 years old at the time of the web survey.

The dependent variable is a watching dummy for each getsuku drama that takes unity when an individual watched the drama at least once during its season. There is the possibility that audience members watch only a few episodes. Such a watching behavior can be informative for our research because the behavior might be associated with low subjective evaluation of the drama. Thus, we include such behavior in the definition of our watching dummy. To keep the sequential order in accumulation of watching experience, we ask only real-time watching behavior and do not count watching after the formal broadcasting period. On the other hand, we allow watching via the internet or recorded video tapes if it occurs during the same period as the broadcast.

An important component for our model is subjective evaluation for watched dramas. Because our web survey is a one-shot survey, this information is interviewed in retrospective questions. We asked for a subjective evaluation as a discrete variable that can be chosen from eleven levels.

In our empirical analysis, we also utilize three demographic characteristics of individuals: gender, age, and education level. For education, we do not ask previous status at the time of watching each drama, to minimize the burden of the interview. Thus, we need to assume time-invariance of these demographic characteristics. The implicit assumption of time-invariance is also assigned for the design of stratified sampling in the sense that the people single at the time of the survey were assumed to be single in the retrospective survey periods. For age, because we do not ask birthday but only asked age at the time of survey, age at the time of the drama broadcast is obtained by subtracting (2013 minus the year of broadcasting) from the age in 2013.

[3]Several novels that share the protagonist with *Galileo* were translated into English and Higashino (2012) in particular was nominated for an Edgar Allan Poe Award for the best mystery novel in 2012.

[4]This number was taken from `http://www.macromill.com/monitor_info/pdf/20130801web.pdf`, accessed on May 9th, 2014

As mentioned in the section 3.1 for model description, we need to discretize all the demographic characteristics in our case-based modeling. Gender takes two values, **Male** and **Female**. Age is decomposed into two statuses: 39 years old or less (**Young**) and 40 years old or more (**Old**). For education level, we utilize two categories: university graduate or more (**University**) and less than university graduate (**High School**). Consequently, we have $2^3 = 8$ categories of demographic characteristics, which we denote as $\mathbf{x}^I$.

Table 1 is around here

The sample size for individuals is $N = 415$. Table 1 reports the descriptive statistics. The subjective evaluation takes value zero for non-watched dramas, whereas it takes eleven values among $\{0.1, 0.2, ..., 1.1\}$ for watched dramas. In demographic characteristics, **Young** reflects the age status at the time of our web survey. We also report the fractions of individuals who compose eight categories of discretized demographic characteristics $\mathbf{x}^I$. As shown in the table, all categories have sufficient numbers of individuals. Also, we summarize information about the number of dramas watched by individuals in Table 1. As shown, approximately 1/4 of individuals did not watch any getsuku dramas, whereas less than 5% of individuals watched 40 or more among the 54 dramas.

3 An empirical model for case-based decision of TV watching

3.1 Model description

We utilize a panel dataset of individuals who choose whether to watch a TV drama or not. The dataset consists of N individuals who are indexed as $i = 1, 2, ..., N$ and T dramas that are sequentially ordered via time index $t = 1, 2, ..., T$. To analyze the watching behavior for the tth drama, the dependent variable is y_{it} that represents a watching decision dummy to take unity when the ith consumer watches the tth drama. Let $\mathbf{x}_t^P$ be a $K \times 1$ vector of drama characteristics that are observable both by consumers and us researchers. We assume that the watching decision is made when the consumer's subjective prediction for his or her own latent utility, y_{it}^*, is nonnegative.

The subjectively predicted utility y_{it}^* is a function of the subjective evaluation of previously watched dramas, denoted by $v_{i\tau}$, where $\tau = 1, ..., t-1$. We define $v_{i\tau} = 0$ for dramas that are not watched. For watched dramas, we define $v_{i\tau} \in [0.1, 0.2, ..., 1.1]$, where a larger number corresponds to higher satisfaction. In the decision making, the subjective evaluation is weighted by similarity in drama characteristics between the τth and the tth drama. The similarity is measured by a similarity function $s_i(\mathbf{x}_t^P, \mathbf{x}_\tau^P)$, which we allow to be individual-specific. The similarity-weighted subjective evaluations for past dramas affect the predicted utility as additively separable terms as well as a constant term that has a coefficient $\tilde{\omega}_0$ and an error term ϵ_{it} that represents unobserved components. In other words,

$$
\begin{aligned}
y_{it}^* &= \tilde{\omega}_0 + \sum_{\tau<t} s_i(\mathbf{x}_\tau^P, \mathbf{x}_t^P) v_{i\tau} + \epsilon_{it}, && (3.1)\\
y_{it} &= I[y_{it}^* \geq 0]. && (3.2)
\end{aligned}
$$

For the similarity function, previous studies commonly adopted a function based on the Euclidean norm for characteristics between dramas. This choice of the similarity function does not fit our data, because we choose only dummy variables for drama characteristics. Instead, we first construct an indicator function which takes unity only when the two dramas both have the same characteristics. For example, if two dramas are both based on novels, then the indicator function regarding **Novel** takes unity. Furthermore, we multiply an individual-specific weight for each pattern of drama characteristics, namely, ω_{ik} for individual i on the $k = 1, ..., K$th drama characteristics. In other words, our similarity function is

$$
s_i(\mathbf{x}_t^P, \mathbf{x}_\tau^P) = \sum_{k=1}^{K} \omega_{ik} I[x_{kt}^P = x_{k\tau}^P = 1], \tag{3.3}
$$

where the indicator function $I[S]$ takes unity if S holds true.

For simplicity, we adopt a parametric assumption for the standard probit model. Specifically, we assume ϵ_{it} to be independent and identically distributed according to the standard normal distribution. Then, our estimands are the coefficient of the constant term ω_0 and K weight terms in the similarity function ω_{ik}. We let $\boldsymbol{\omega}_i = (\tilde{\omega}_0, \omega_{i1}, ..., \omega_{iK})$ and refer to it as a coefficient vector. As a result, the estimation model is the following simple linear model.

$$
y_{it}^* = \mathbf{x}_{it}' \boldsymbol{\omega}_i + \epsilon_{it}, \tag{3.4}
$$

where

$$
\mathbf{x}_{it} = \Big\{1, \sum_{\tau<t} I[x_{1t}^P = x_{1\tau}^P = 1] v_{i\tau}, ..., \sum_{\tau<t} I[x_{Kt}^P = x_{K\tau}^P = 1] v_{i\tau}\Big\}'. \tag{3.5}
$$

To understand more details about case-based models in empirical situations, we adopt two specifications on $\boldsymbol{\omega}_i$. The first specification is a pure case-based model which does not utilize any individual-specific information other than the subjective evaluations for previously watched dramas. Thus, we have $\boldsymbol{\omega}_i = \boldsymbol{\omega}$ for any i.

In the second specification of a case based model, the weight terms of the similarity function are allowed to depend on demographic characteristics of individuals. For simplicity, we do not assume that weights for all drama characteristics vary with all individual characteristics, but adopt the following schemes. First, the weight for **Novel** does not depend on demographic information, because we do not have intuition for demographic variation of the effects of this variable. Second, for cast effects of **Johnny's** and **Kimutaku**, weight terms can differ in terms of gender, because these variables are concerned with actors. Finally, **Comedy**, **Love**, and **Mystery** can depend on all demographic characteristics.

To see the validity of the case-based model, we compare its performance with that of a conventional utility-based model. The utility-based model is assumed to be a linear probit model in which consumer and drama characteristics, $\mathbf{x}_i^I$ and $\mathbf{x}_t^P$, and their cross terms are included in explanatory variables but subjective evaluations are not. On the choice of cross terms, we utilize the combinations corresponding to those for the above case-based model with demographic information. Specifically, we utilize **Female** times **Johnny's** and **Kimutaku**, and all demographic characteristics times drama themes, **Comedy**, **Love**, and **Mystery**. We compare the case-based and this utility-based models using the Akaike Information Criterion (AIC) and Schwartz's Bayesian Information Criterion (BIC).

3.2 Prediction analyses

In addition to the model selection via AIC and BIC, we also conduct two schemes for prediction analysis of the choice probabilities of watching dramas. The first scheme is one-step-ahead prediction. This prediction scheme separates dramas into two groups of samples for estimation and for prediction, whereas it utilizes all individuals for both estimation and prediction. We adopt the first T_e dramas for the estimation sample and the $(T_e + 1)$th drama for the prediction sample. We separately conduct four prediction analyses for $T_e + 1 = 51, 52, 53, 54$.

The second prediction scheme is an out-of-sample type method. The out-of-sample prediction separates individuals into estimation and prediction samples, whereas it utilizes all dramas for both estimation and prediction. In the straight-forward adoption of the out-of-sample prediction into the case-based model, we need to know subjective evaluations for watched dramas for all individuals in the prediction sample. If one tries to conduct prediction for audience rate among general population, it is burdensome to obtain such individual-level information for the prediction sample.

Instead, we consider a practical method of out-of-sample type prediction where the aggregate data among the estimation sample is used to mimic individual subjective evaluations. Specifically, we utilize the mean of subjective evaluations of individuals in the estimation sample for each drama. For the model with demographic information, we take the mean among individuals in the estimation sample who share the demographic characteristics $\mathbf{x}^I$ depending on the drama characteristics. Specifically, we utilize the average of all individuals for **Novel**, gender-specific averages for **Johnny's** and **Kimutaku**, and average for all demographic characteristics for **Comedy**, **Love**, and **Mystery**. Let $\bar{v}_{i\tau,k}^E$ be the average subjective evaluation that corresponds to the kth drama characteristics. Given the coefficient estimates $\hat{\boldsymbol{\omega}}_i$, the predicted choice probabilities for drama t and individual i, who belongs to the prediction sample, is

$$\widehat{Pr(y_{it}^* = 1)} = \Phi(\tilde{\mathbf{x}}_{it,P}' \hat{\boldsymbol{\omega}}_i), \tag{3.6}$$

where

$$\tilde{\mathbf{x}}_{it,P} = \Big\{1, \sum_{\tau<t} I[x_{1t}^P = x_{1\tau}^P = 1]\bar{v}_{i\tau,1}^E, ..., \sum_{\tau<t} I[x_{Kt}^P = x_{K\tau}^P = 1]\bar{v}_{i\tau,K}^E\Big\}'. \tag{3.7}$$

3.3 Distinct properties of our model in the literature

Our model has several differences from the previous empirical studies of case-based models in the following two points. First, we do not utilize the empirical similarity model[5] of Gilboa et al. (2006), in which the latent utility takes the following form.

$$y_{it}^* = \frac{\sum_{\tau<t} s(\mathbf{x}_t^P, \mathbf{x}_\tau^P) v_{i\tau}}{\sum_{\tau<t} s(\mathbf{x}_t^P, \mathbf{x}_\tau^P)} + \epsilon_{it}. \tag{3.8}$$

We instead utilize a simple linear probit model to achieve flexibility in empirical analysis. As a result of our modeling, we have a different interpretation for weight ω_{ik}. In the original model, the weight terms can be naturally interpreted as a measurement of similarity. In our model, the weight can also reflect individual taste for drama characteristics. Specifically, we allow $\omega_{ik} < 0$, for which the similarity in unfavored components reduces the predicted utility. Therefore, we can interpret the coefficients $\boldsymbol{\omega}_i$ as effects of drama characteristics on watching behavior, in a manner similar to that of the coefficients for the utility-based model.

Second, the determination of v_{it} is not explicitly modeled in our model set-up. In the conventional utility-based model, v_{it} and the latent utility are directly related. On the other hand, in the case-based model, predicted and realized utilities are not required to be equivalent. This point did not appear in the previous work by Gayer et al. (2007) in which they used the same variable on the left-hand side and right-hand side, because they analyzed prices, not utility.

4 Empirical results

4.1 Estimation results

Table 2 is around here

Table 2 reports the probit estimation results for two specifications of our case-based model. Columns (1) and (2) represent the pure case-based model without demographic information and the case-based model with demographic information, respectively. We omit to show the coefficient estimates for the utility-based model.

For the statistical model selection, the most important topic is the comparison of the case-based and utility-based models. The utility-based model exhibits 21,172 and 21,222 for AIC and BIC, respectively. According to both information criteria, case-based models, either with or without demographic information, are preferred in the statistical model selection. This result clearly shows the validity of the case-based model for TV watching behavior.

[5]We also tried estimation with the empirical similarity model, but our estimation for the specification with demographic information yielded large standard errors for estimators, and so we do not utilize this model in our empirical analysis. It seems that the sample size of our data is not enough to have sharp identification for the complicated functional form of the empirical similarity model.

The model selection can also provide a comparative study of the case-based models with and without demographic information. As a result, AIC chooses the model with demographic characteristics, whereas BIC chooses the pure case-based model without demographic information. This result might be caused by the difference in penalty terms for the definitions of AIC and BIC, which result in BIC preferring a simpler model[6]. In short, it might imply that these two specifications do not differ much as statistical models, and that the case-based model is a powerful empirical model even without demographic information.

For coefficient estimates, we have the following implications. First, for the case-based models, all coefficients have positive estimates and are significant except for the coefficients of **Johnny's** in the model with demographic information. Because all elements of $\boldsymbol{x}_{it}$ take nonnegative values by definition, the positive signs of coefficients indicates that watching a drama always increases the probability of watching future dramas. This situation is similar to the rational addiction model Becker and Murphy (1988) in which consumers increase their ability to enjoy a good through their own consumption experience. Also, this is consistent with the finding in Table 1 that approximately 1/4 of individuals did not watch any getsuku dramas. This large number of non-watchers might imply that the first watching is important for further accumulation of watching experience[7].

Second, in the comparison of case-based models with and without demographic information in (1) and (2) in Table 2, we obtain similar estimates. We also see in (2) that there is no large difference among coefficient estimates for each pattern of drama characteristics by demographic characteristics. This observation also implies that the influence of demographic factors is small for the case-based model in watching getsuku dramas.

For each drama characteristic pattern, **Novel** has a significantly positive effect. Dramas in this category are generally based on bestsellers and have already obtained popularity before the TV version is broadcast. Thus, it is natural to have a positive coefficient for this variable. For cast variables, effects for **Johnny's** and **Kimutaku** do not exhibit a gender difference. There must be enthusiastic female fans for these male cast members, but considering the wide popularity of getsuku dramas among the general Japanese population, these admirers have rather minor impacts. Furthermore, the large positive effect of **Kimutaku** and the small effect of **Johnny's** imply that the popularity of Takuya Kimura is much greater than that of the other actors who are managed by Johnny & Associates.

For drama themes, although the difference is small, **Mystery** is more popular for young audience members than for older members in every gender and education group. This result implies that the recent popularity of mystery dramas, which was mentioned earlier, might be based on the support by young audience members. On the other hand, we do not find a particular demographic pattern with a taste for **Comedy** or **Love**.

[6] More formal discussion comparing AIC and BIC is given in Burnham and Anderson (2002)

[7] To investigate the general individual-specific taste about watching getsuku, we also tried to analyze a model with individual fixed effects. However, because several individuals did not watch any dramas, a multicollinearity problem prevents us from conducting prediction analysis.

4.2 Prediction results

We utilize two methods to report results of prediction analysis. First, we show the mean squared errors (MSE) of predicted choice probabilities for watching dramas. The predicted choice probabilities are obtained by plugging the coefficient estimates into the choice probability of the probit model. Second, we also consider group-mean choice probabilities for those who actually watched a drama and those who did not. For a good predictor, we expect there to be a positive difference between the choice probabilities of watched and non-watched groups.

Table 3 is around here

Table 3 shows the prediction results. (1), (2), and (3) represent the pure case-based model, the case-based model with demographic information, and the utility-based model, respectively.

For one-step-ahead prediction, the most important finding of our study is that case-based models outperform the utility-based model. For the MSE, the utility-based model shows larger values than any specification of case-based models in all dramas. For group means of choice probabilities, the utility-based model shows similar means for those who actually watched dramas and those who did not, whereas the case-based models indicate a large positive difference in choice probabilities between watched and non-watched groups. Specifically, the probability difference is 1 to 2 percent points for the utility-based model, whereas it is 20 to 50 percent points for the case-based models. These results are consistent with our finding on the superiority of case-based models in the statistical model selection.

For one-step-ahead prediction among the case-based models, the model without demographic variables achieved smaller MSEs for three dramas, $T_e + 1 = 51, 53, 54$, and a similar MSE for $T_e + 1 = 52$. Thus, the model without demographic information has better prediction performance than the model with demographic information. This result shows the minor role of demographic information, provided that we have individual-level information on subjective evaluation.

The remaining question is whether we can mimic the individual-level information with aggregate-level information, which is the purpose of our out-of-sample type prediction. For out-of-sample type prediction, we randomly choose 100 individuals for the prediction sample and distribute the remaining individuals as estimation samples. In the 5,400 ($= 100 \times T$ and $T = 54$) prediction sample, 704 observations are watchers and 4,696 observations are non-watchers.

In out-of-sample type prediction, case-based models show such poor performances that they are outperformed by the utility-based model, in contrast to the results for model selection and one-step-ahead prediction. In the MSE, the utility-based model shows the smallest prediction errors. Also, case-based models do not show a large difference in the mean choice probabilities between watched and not-watched samples. Specifically, the probability difference is approximately 5 percent points for the utility-based model, whereas it is 0.5 or 1.5 percent points for the case-based models.

These results imply that we cannot replace the individual subjective evaluations by demographic information and aggregate data. Therefore, the good performance of the case-based model in statistical model selection and one-step-ahead prediction might depend on the availability of individual subjective evaluations, which imposes a burden for data collection.

4.3 Extensions

In this subsection, we utilize two extensions to our basic model, which are possible owing to the flexibility of our linear probit model. Specifically, we consider a premium for recently watched dramas and inclusion of the published audience rate as an explanatory variable. These analyses are adopted for a purely empirical reasons and are not guaranteed to satisfy the axioms of consumer decision. The theoretical justification is a task remaining for future research. Good performance observed for these extensions shows preferable directions for extension in theoretical studies of case-based modeling. We introduce the following extensions into the pure case-based model in which $\boldsymbol{\omega}_i = \boldsymbol{\omega}$[8].

First, we introduce a special treatment for recently watched dramas. All previous experience is equally weighted in the original case-based decision making. However, it is natural that audiences are more affected by recent dramas, which are fresh in their memories. To adopt such an effect, we multiply the similarity function by an additional variable $\alpha > 0$ when the $\tau-$th drama was broadcast within the previous year. Because there are four getsuku dramas per year, dramas in the previous year are identified by $t - \tau \leq 4$. Thus, our new similarity function becomes

$$s_i(\mathbf{x}_t^P, \mathbf{x}_\tau^P) = \alpha^{I[t-\tau\leq 4]} \sum_k \omega_{ik} I[\mathbf{x}_{kt}^P = \mathbf{x}_{k\tau}^P = 1]. \tag{4.1}$$

In this new model, $\alpha = 1$ means the recent dramas have the same effects as less recent programs, whereas $\alpha > 1$ means that recent programs are more influential.

Second, we adopt the audience rate of dramas to control two elements. The first element is peer effects. The audience decision can be influenced not only by learning through their own experiences but also by social learning as in Moretti (2011), an empirical study of movie ticket sales using social learning. We eliminate peer effects from family members which were analyzed by Yang et al. (2006) by restricting our sample to single households. However, more general peer effects, such as those from colleagues and neighbors, cannot be avoided in our basic model. A main reason to include the audience rate is to capture such peer influence. Peer effects might be associated with person-to-person communication after the beginning of broadcasting. In our definition of the variable, the drama watching dummy takes unity if an individual watched a drama at least once. This definition can capture an audience who starts watching a drama from the second or later episode, as a result of peer effects.

We can interpret that this specification with audience rate implies a hybrid model of learning from own experience in the case-based modeling and social learning from

[8] We also introduced these extensions into the case-based model with demographic variables. Because the results were similar to those for the pure case-based model, we omit reporting them here.

peers[9]. There can be interaction between these two learning mechanisms, but detailed consideration of such theoretical study is beyond the scope of this article.

The audience rate can also control impacts from the other TV programs in the 9pm Monday timeslot. There can be competition between TV networks for timeslots, like that analyzed in Goettler and Shachar (2001). The existence of a strong rival can be partially captured by a low audience rate.

Table 4 is around here

Table 4 reports the estimation and prediction results for the extended models. (4) shows the results for the model with the premium for recent programs, whereas (5) shows the results for the model with the published audience rate.

For estimation results, (4) shows that the estimated value of α is significantly positive. Furthermore, the one-sided test for the hypothesis of $\alpha > 1$ is not rejected at the 0.01 significance level. This result implies the existence of a strong premium for recently watched dramas in case-based decision making. In the case of (5), the estimated coefficient for the published audience rate is shown to be significantly positive. This result is naturally interpreted as either a positive peer effect or existence of premium from absence of a strong rival.

For the performance of models, we have that both of the extended dramas outperform the basic case-based models in Tables 2 and 3. AIC, BIC, and one-step-ahead prediction results show better performance of extended models than basic case-based and utility-based models. Furthermore, the out-of-sample type prediction is also improved. The MSE for the model with α is smaller than the utility-based model, whereas the MSE for the model with the published audience rate is similar to the utility-based model. In both models, there is a large positive difference between group means of predicted choice probabilities for watchers and non-watchers. These results indicate the importance of the extended models in the empirical analysis. Considering the fact that these improvements can be achieved by small changes to the basic case-based model, such extensions might be valuable for further theoretical research.

5 Conclusion

This study empirically analyzed audience behavior for Japanese TV watching using a case-based decision model. We constructed a simple linear probit model and proposed prediction methods for audience rates. Our empirical analysis showed the superior performance of our model in comparison with a conventional utility-based model. The case-based model is revealed to be such a powerful model for TV watching behavior that it can work well even without consumer characteristics other than individual subjective evaluations. We also considered two extensions that are not guaranteed to satisfy the axioms of consumer decision, but our extended models have important empirical

[9] Kinjo and Ebina (2014) estimated a hybrid model which contains a state-dependent term and audience rate under similar motivations to that in this article.

implications and achieved good performance. We believe that further studies involving collaboration between theoretical and empirical researchers can extend the frontier of consumer analysis.

A potential weakness of this study is the small sample size in both the number of individuals and the coverage of TV programs. For individuals, the limited sample size restricts the number of discretized categories for demographic characteristics, despite that we originally have finer information. On the coverage of programs, although our research concentrated on the getsuku dramas, there can be influence by other drama programs. This is indicated by the fact that there was no actress who appeared in more than three getsuku dramas as a main character. It would not be natural that drama producers to ignore the influence of actresses on TV watching behavior. Thus, this observation might imply that the popularity of actresses, at least in youth-oriented dramas such as getsuku, vanishes quickly. Thus, it might be important to consider the many drama programs which are broadcast at the same time as getsuku.

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Figures and tables

		Observation	Mean	S.D.
Drama watching dummy (y)		22410	0.19	(0.40)
Subjective evaluation ($v \in \{0, 0.1, ..., 1.1\}$)		22410	0.16	(0.34)
Subjective evaluation of watchers (v given $y = 1$)		4336	0.81	(0.23)
Drama	Novel	54	0.13	(0.34)
Characteristics	Johnny's	54	0.33	(0.48)
	Kimutaku	54	0.13	(0.34)
	Comedy	54	0.28	(0.45)
	Love	54	0.57	(0.50)
	Mystery	54	0.19	(0.39)
	Published audience rate (%)	54	17.01	(4.31)
Demographic	Female	415	0.4	(0.49)
Characteristics	Young	415	0.47	(0.50)
	University	415	0.48	(0.50)
Count for $\mathbf{x}^I$	F, Y, H	39		
	F, Y, U	36		
	F, O, H	69		
	F, O, U	22		
	M, Y, H	54		
	M, Y, U	66		
	M, O, H	53		
	M, O, U	76		
#Drama watched		415	10.45	(11.99)
#Individuals	#Watched drama=0	94		
	0<#Watched drama≤10	175		
	10<#Watched drama≤20	66		
	20<#Watched drama≤30	48		
	30<#Watched drama≤40	16		
	40<#Watched drama	16		

Table 1: Descriptive statistics. F, M, Y, O, U and H are short for Female, Male, Young, Old, University and High school, respectively.

Dependent variable: Drama Watching Dummy					
Drama	Demographic	(1)		(2)	
Novel	All	0.067***	(0.010)	0.068***	(0.010)
Johnny's	All	0.003*	(0.002)		
Johnny's	Female			0.002	(0.003)
Johnny's	Male			0.004	(0.003)
Kimutaku	All	0.088***	(0.005)		
Kimutaku	Female			0.084***	(0.007)
Kimutaku	Male			0.091***	(0.007)
Comedy	All	0.046***	(0.002)		
Comedy	F, Y, H			0.050***	(0.004)
Comedy	F, Y, U			0.046***	(0.004)
Comedy	F, O, H			0.035***	(0.006)
Comedy	F, O, U			0.035***	(0.009)
Comedy	M, Y, H			0.044***	(0.005)
Comedy	M, Y, U			0.045***	(0.005)
Comedy	M, O, H			0.052***	(0.009)
Comedy	M, O, U			0.064***	(0.007)
Love	All	0.030***	(0.001)		
Love	F, Y, H			0.032***	(0.002)
Love	F, Y, U			0.034***	(0.002)
Love	F, O, H			0.030***	(0.003)
Love	F, O, U			0.019***	(0.004)
Love	M, Y, H			0.026***	(0.002)
Love	M, Y, U			0.025***	(0.002)
Love	M, O, H			0.038***	(0.004)
Love	M, O, U			0.032***	(0.003)
Mystery	All	0.088***	(0.005)		
Mystery	F, Y, H			0.091***	(0.010)
Mystery	F, Y, U			0.099***	(0.009)
Mystery	F, O, H			0.083***	(0.009)
Mystery	F, O, U			0.074***	(0.016)
Mystery	M, Y, H			0.093***	(0.010)
Mystery	M, Y, U			0.090***	(0.009)
Mystery	M, O, H			0.089***	(0.013)
Mystery	M, O, U			0.077***	(0.009)
NT		22,410		22,410	
AIC		18751		18746	
BIC		18767		18816	

Table 2: Marginal effects of probit model for case-based models. (1) and (2) represent the pure case-based model and the case-based model with demographic information, respectively. F, M, Y, O, U, and H are short for Female, Male, Young, Old, University, and High school, respectively. Standard errors in parentheses. $***$, $**$, and $*$ denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

		Average watching dummy of prediction sample	MSE	Mean of predicted choice probabilities y=1		y=0	
One-step-ahead							
$T_e + 1$=51		0.267					
	(1)		0.149	0.364	(0.232)	0.156	(0.109)
	(2)		0.152	0.364	(0.252)	0.158	(0.112)
	(3)		0.217	0.123	(0.039)	0.114	(0.400)
$T_e + 1$=52		0.227					
	(1)		0.162	0.820	(0.251)	0.320	(0.283)
	(2)		0.162	0.816	(0.252)	0.319	(0.282)
	(3)		0.199	0.371	(0.068)	0.367	(0.067)
$T_e + 1$=53		0.253					
	(1)		0.164	0.619	(0.281)	0.291	(0.244)
	(2)		0.165	0.611	(0.284)	0.288	(0.245)
	(3)		0.188	0.254	(0.068)	0.239	(0.063)
$T_e + 1$=54		0.439					
	(1)		0.148	0.555	(0.258)	0.190	(0.148)
	(2)		0.149	0.553	(0.262)	0.188	(0.145)
	(3)		0.278	0.256	(0.066)	0.237	(0.058)
Out-of-sample		0.215					
	(1)		0.123	0.204	(0.081)	0.199	(0.076)
	(2)		0.123	0.213	(0.099)	0.199	(0.086)
	(3)		0.115	0.251	(0.084)	0.202	(0.076)

Table 3: Prediction results. (1), (2), and (3) represent the pure case-based model, the case-based model with demographic information, and the utility-based model, respectively. Standard deviations in parentheses.

Estimation			Estimate(S.E.)			Model Selection	
			α	Audience rate		AIC	BIC
		(4)	5.191***(0.296)			17242	17261
		(5)		0.022***(0.001)		18207	18226
Prediction			MSE	Mean of predicted choice probabilities			
				y=1		y=0	
One-step-ahead	$T_e + 1$=51	(4)	0.125	0.299	(0.384)	0.146	(0.189)
		(5)	0.164	0.307	(0.277)	0.081	(0.118)
	$T_e + 1$=52	(4)	0.128	0.323	(0.398)	0.159	(0.210)
		(5)	0.139	0.746	(0.263)	0.276	(0.255)
	$T_e + 1$=53	(4)	0.119	0.315	(0.409)	0.137	(0.173)
		(5)	0.150	0.456	(0.310)	0.157	(0.209)
	$T_e + 1$=54	(4)	0.114	0.370	(0.448)	0.156	(0.203)
		(5)	0.128	0.678	(0.258)	0.249	(0.183)
Out-of-sample		(4)	0.094	0.329	(0.409)	0.032	(0.083)
		(5)	0.116	0.254	(0.142)	0.184	(0.112)

Table 4: Results for extended models. (4) and (5) represent models with a premium for recently watched dramas and with published audience rate, respectively. The coefficient estimate for (5) shows the marginal effect of probit estimation. Standard errors for estimation and standard deviations for prediction in parentheses. *** in estimation denotes $p < 0.01$.