A Group Decision Making Approach to Model Household TV Channel Choice

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ABSTRACT

An accurate television viewing choice model is an important tool for television industry executives, as well as advertisers. An efficient model can help television channels maximize ratings by improving both scheduling and the characteristics of their shows. On the other hand advertisers can predict ratings and demographic composition of audiences with better accuracy. Though there is considerable evidence to suggest that individual viewing choices are strongly affected by one's family members, quantitative models in marketing literature typically focus on the individual as the unit of analysis without incorporating the influence of family members.

This thesis proposes a three-stage model to capture the process of household television viewing behavior. We divide the household viewing process into three sequential and interrelated decision stages (pre-decision, joint decision, and final-decision) according to the group decision making framework suggested in prior research. By defining utilities of different programme types on different channels, and weighting parameters of each family member, each family member's three decisions (pre-decision, joint decision and post-decision) are modeled as a function of these parameters with three sub-models. The model was estimated with maximum likelihood estimation, duly validated with simulation studies. Meanwhile, the model was extended to be time-dependent to allow past viewing history to influence current viewing choice, and applied on the people meter data for primetime telecasts on weekdays for the whole of 2006. The results indicate that our model has better prediction accuracy compared with models being currently used (Rust and Alpert 1984; Yang et al. 2010). Furthermore, we are able to demonstrate that models that ignore the influence of family members yield biased estimates. Our model also has better prediction accuracy compared with the traditional model proposed by Rust and

Alpert (1984), and has more flexibility to fit households with different compositions. Finally, we find that there exist different household decision structures, initial latent preferences, and influences of past viewing history across different families and their members, and the heterogeneity can be explained by demographic variables.

Key Words: viewing choice modeling, television rating, group decision making

(342 words)

ABSTRACT (CHINESE)

准确的电视收视率预测对电视从业者和电视广告商来说是非常重要的。准确的电视收视率预测模型可以帮助电视从业人员通过调整电视节目次序和电视节目的特点来提高电视收视率，同时也可以帮助电视广告商预测电视收视率和观众背景。虽然有很多的事例证明个人频道选择强烈的被其他家庭成员影响，现存的数学模型只是针对个人为分析单位，没有将家庭成员之间的互相影响考虑其中。

在本篇论文中，我提出了一个包括三步骤的模型来模拟家庭成员频道选择行为。首先，家庭电视收视行为可以被分解成三个相互联系在一起的分模型（初决策分模型，联合决策分模型，终决策分模型）。通过定义不同电视节目的效用函数以及家庭成员的权重，每位家庭成员的初决策，联合决策，最终决策可以推算出来。我们用最大似然估算方法对模型进行优化，并通过模拟数据对这种优化方法进行验证。同时，模型还被推展到时间动态模型，允许之前的收视行为影响现在的收视行为。我们把这个模型应用于 2006 年黄金时段的人员收视统计数据上。我们发现，相较于电视从业人员常用的预测模型，这个模型可以有更准确的预测。因此电视从业人员也可以应用这个模型来进行更准确的预测。另外，相较于没有考虑家庭成员相互影响的模型，这个模型可以提高对家庭成员电视频道选择行为的预测。这个模型可以提供高于之前文献 (Rust and Alpert, 1984) 中的预测率，并可适用于不同的家庭结构。最后，我们发现家庭电视频道决策结构，每个人的潜在效用函数，以及过去收视行为的影响都在各个家庭中，各个家庭成员中有不同的模式。这些不同的模式可以由家庭成员的人口统计变量进行解释。

关键词：电视收视模型，电视收视率，群体决策

(651 字)

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CHAPTER 1 INTRODUCTION

Members of the advertising industry know the tremendous economic implications of television ratings. Millions of dollars are at stake because advertising rates are the function of television ratings. To accurately predict television ratings of a programme, we need to consider the programme type, the channel on which it is aired, the family influence and the past viewing behavior of the target audience. The objective of the current research is to build an integrated statistical model to incorporate the above factors, which is then applied on by-minute people meter viewing records.

1.1 The Television Rating Business

Over the last half-a-century or so, television has established itself as one of the most important mass media, dominating leisure hours and family life. It ranks as the most pervasive leisure-time activity in the United States (Frank and Greenberg, 2000). Television stations sell television time (in fact, the audiences that watch specific programmes) to advertisers, who want their advertisements to be shown to the targeted population (Ang, 1990). The number of viewers who watch programmes of a TV channel are the principal factor that determines a television station's revenue. Television stations, therefore, try to attract the maximum number of viewers to watch their programmes since the rates they can charge for commercials embedded in programmes are directly proportional to the number of viewers. Figure 1.1 illustrates the relationships between viewers, television stations, and advertisers.

Television has become a large business in U.S. Based on recent statistics, television advertising revenues are approximately US$ 16 billion per year (www.thepowerinfluence.typepad.com), which explains the scramble for ratings. Advertising revenue accounted for almost fifty percent of the yearly revenue for CNN in the year 2009 (http://www.mediabistro.com). Advertisements between telecast of The Super Bowl, one of the most favorite television programmes in US, typically cost millions of dollars. A 30 second advertisement during the 2010 Super Bowl telecast cost US $2.6 Million (http://en.wikipedia.org). In a developing country like China, television advertising revenues are approximately US$ 65 billion per year (www.iresearch.com). CCTV, the largest network in mainland China, received US$ 1.6 billion in advertising revenues in year 2010, and its largest advertiser MengNiu spent US$ 30 million in 2010. During the most popular television programme the Spring Festival Gala Evening, the total advertising revenue was US$ 73 million in 2010 with a 10 second advertising spot at 12 p.m. costing as high as US$ 7.7 million; the rate depends on the audience size attained by the programme and the profile of the viewers (www.zongyiweekly.com).

---Insert Figure 1.1 about here---

1.2 The Need for Accurate Prediction of Television Ratings

Given the economic and social implications of television ratings, accurate rating prediction is of utmost important as any discrepancy between predicted and actual ratings leads to direct losses for advertisers.

Overestimation of expected viewership of a programme can push up costs for advertisers since advertising slots are generally purchased in advance of telecast.

Although "make-goods" (free advertising time on other programmes when programmes do not achieve the projected rating) are typically made available to advertisers if a programme fails to attain the expected rating in some countries (e.g., England, the United States), the compensatory slots are not always consistent with advertisers' objectives. Furthermore, this kind of approach is not available in Asian countries like China. Thus, advertisers in Asia would rather "get it right the first time," i.e. better predict viewers' choices and ratings and then develop the media schedule. Rating prediction is a major concern during the buying period in which advertisers must guess how the networks' new schedules will fare.

Underestimation, on the other hand, is equally undesirable as it results in loss of revenue for television stations.

To conclude, accurate television rating predictions is crucial for both advertisers and television stations. However, there are several limitations in the current industry practices, as well as extant academic research.

1.3 Gaps in Extant Research

Two sources of data are usually available for predicting television ratings: self-reported surveys and electronic monitoring. The collection of viewing data by using self-reported survey, or consumer diary, dates back to the 1960's. The survey approach has been criticized for its inaccuracy and for being expensive (Barwise and Ehrenberg, 1988; Meneer, 1987). For example, some of the attempts to measure the husband's influence are undoubtedly biased by social desirability. A wife does not want to admit that her husband's opinion on a channel or a programme was not important to her or that she did not take her husband's preferences into account (Davis, 1976). The other approach is to capture viewing records electronically (e.g., the People Meter System; see detailed information in Appendix 1). Electronic meters are installed in sample households and the time and duration of each programme a viewer watches is recorded automatically. People meters are now being used to measure television ratings by both industry and academia.

Conversations with television station schedulers and researchers in major corporations in Hong Kong and Mainland China (e.g., AC Nielsen and Hong Kong Television Broadcasting Ltd.) indicate that research being done in this area is quite limited, and only simple statistical analysis is being used to predict ratings. The most commonly used methodology is frequency count, in which researchers predict future viewing choices of individuals or families based on their most frequently watched channels or programmes in the recent past. This prediction method is normally adjusted for time of the day (the most frequently selected viewing choices in different time ranges in previous days are summarized, and are used to predict future viewing choices during the same time range in later days) or by programme types (the most frequently selected viewing choices in terms of different programme types in previous days are summarized, and are then used to predict future viewing choices of different programme types in later days). However, these frequency counts can not provide adequately accurate television ratings predictions.

With the development of the people meter system, academic research in this area has started flourishing. Statistical models are being formulated to predict viewing choices either at individual-level or aggregate-level. Earlier research has found that programme characteristics, including programme types (Bowmen and Farley, 1972; Lehmann, 1971) and the channels (Rosengren and Windahl, 1972; Owen et al., 1974) may affect programme choice. Other research suggests that past viewing behaviors, sometimes as state dependence effect, is another key variable to influence viewing choice (Leone, 1995; Moshkin and Shachar, 2002; Rust, Kamakura and Alpert 1992; Sang et al., 1994; Shachar and Emerson, 2000).

Interactions among family members are assumed to be strong due to cohabitation and strong emotional ties, and hence some recent research works have also studied the interactions among household members during television viewing (Yang, Narayan and Assael 2006; Yang et al., 2010). However, the factors pointed out in prior research have never been incorporated together as an integrated model for television rating prediction. In addition, little research has been conducted to examine the influence of interactions among family members on TV ratings. Also, most statistical models lack explanatory power for the decision process which is also very important to marketers. For example, how do the family members resolve conflicts during the television viewing process? Who is normally the decision maker? And are there any interactions among family members? These questions haven't been answered clearly by prior research.

1.4 Research Objectives

We believe a model integrating programme characteristics, channel reputation, past viewing behavior, and family influence simultaneously can accurately forecast television ratings. In addition, we want to demonstrate the decision process among family members to fill in the gap in prior literature.

The objectives of this research are to:

1. Build an integrated statistical model to incorporate different factors that influence the television viewing process and the choice of programmes or channels, and

construct a solid methodology to estimate the above model.

2. Test the explanatory and predictive power of the model on recent people meter data.

We propose a three-stage model using a group decision making approach to describe how each family member makes viewing choice. The model is also extended to allow past viewing behaviors to impact current viewing choice. We first apply the model on simulated data to verify the estimation methodology. After that, we apply the model on recent viewing records in Hong Kong market. We demonstrate that the proposed model and the associated methodology can achieve high prediction accuracy rate. The model can help practitioners decide the channel, the programme, and the timeslot for placing advertisements. More importantly, we find that models ignoring the family influence can yield biased estimates of consumers' true viewing decisions. In addition, the estimated parameters clearly depict the decision process which can provide realistic managerial implications for both advertisers and channels. For example, who is the key decision maker during family television viewing? How does the household decision making process vary across different households? How would different family members react towards the joint household decision? How individual family members' preferences vary across different types of programmes and channels? How does past viewing behavior impact choice of programme or channel for different family members? Finally, do the decision process and other viewing behaviors vary across families, and can the heterogeneity be explained on the basis of demographic characteristics of families and their members?

The remainder of this paper is organised as follows. In Chapter 2, we review the literature on television viewing choice and group decision making. In Chapter 3, we develop a static, household-level probability model by treating household television viewing as a three-stage group decision making process. We introduce the model estimation method, and validate the estimation method via simulation. In Chapter 4, we extend the static model to be time-dependent by incorporating past viewing behavior. In Chapter 5, we demonstrate the model application process, and illustrate the results in one representative family. In Chapter 6, we summarize the empirical results after applying the proposed model, including behavioral interpretation of estimated parameters, and report prediction power. Lastly, in Chapter 7, we conclude with a discussion of our contributions and managerial implications, limitations, and future research directions.

CHAPTER 2 LITERATURE REVIEW

Our study draws upon two streams of literature: modeling of television viewing choice and modeling of the group decision making. In this chapter, we first review the literature on television viewing choice modeling to illustrate developments in this field. We further review literature related to programme characteristics, the effect of past viewing behavior, and the family influence. We also summarize the relevant literature on group decision making, and differentiate it from research on preference interdependence.

2.1 A Tour of Television Viewing Choice Modeling

The new data capture technology (people meter) allows researchers to predict television viewing choices by constructing comprehensive and reliable statistics, which is resulting in more empirical studies for modeling of television ratings. These empirical models can be divided into aggregate and individual-level models.

2.1.1 Aggregate Model

Aggregate models (also termed as "ratings models") that predict aggregated viewing choices for a group of people have been proposed by Darmon (1976), Gensch and Shaman (1980), Henry and Rinne (1984), etc. Early literature includes work by Darmon (1976), who used a regression model to relate viewing choice to programme type and channel loyalty, and Zufryden (1973), who incorporated inertia as a major factor determining viewing behavior. Horen (1980) made a partial allowance for these effects by including a lead-in variable in his aggregate model. Gensch and Shaman (1980a, b) used a trigonometric progression model applied to time series data to predict channel shares, partly on the basis of prior audience data. Henry and Rinne (1984) used an aggregate viewing choice model to predict channel shares that different programme types receive.

However, the problem with aggregate models from the advertisers' point of view is their lack of insight into how programmes reach specific target socioeconomic groups because different segments have very different viewing patterns (Bower, 1973; Rust and Alpert, 1984). Actually, many aggregate audience exposure models have demonstrated different exposure probabilities for different individuals (Greene and Stock, 1967; Chandon, 1976; Rust and Klompmaker, 1981). These models reflect that individual differences occur in viewing choice, which fuels the development of individual-level viewing choice model.

2.1.2 *Individual-level Model*

Pioneering work in the area of individual-level viewing choice model was done by Rust and Alpert (1984). The authors specified the utility of viewing a programme as a function of demographics, categories of TV programmes, and an "audience flow state" variable that represents TV-related characteristics. Rust and Eechambadi (1989) extended the above model to account for popularity of particular programmes in particular audience segments. Audience composition and programme types were explicitly incorporated into their model. Rust, Kamakura and Alpert (1992) first built a multidimensional scaling map for programmes, based on similarity of viewers' choices. They then used this space to develop a viewing choice model. In addition, segment-level logit model is used to model the on-off decision. Tavakoli and Cave (1996) proposed a dynamic logit model of viewing behavior, which relates channel choice to programme types that competing channels offer. Shachar and Emerson (2000) extended Rust and Alpert (1984) by 1) introducing a new programme characteristic: demographic characteristics of a programme's cast; 2) allowing preferences over traditional show categories to be a function of both observable and unobservable individual characteristics; and 3) allowing the cost of switching among viewing alternatives to vary across show types and individual characteristics.

More recently, Danaher and Mawhinney (2001) used experimental data to develop a method for rescheduling of TV programmes to maximize the total viewership for one television network across one week. Specifically, they developed a latent class multinomial logit model for modeling viewing preferences. Goettler and Shachar (2001) specified a structural model of TV programme choices that explicitly considers competition among shows and state dependence in choice. This model is used to estimate latent programme attributes and to compute Nash equilibrium of a programme location game. They found that channel's scheduling strategies were generally optimal. Moshkin and Shachar (2002) found that viewers' utilities of viewing choices depend not only on their previous programme choices, but also on the dependence of their information sets on their previous choices. Godes and Mayzlin (2004) found that word of mouth has explanatory power in a model of television ratings. Liu et al. (2004) theoretically modeled the competition between commercial television broadcasters and found that having more channels does not necessarily maximize viewer welfare.

2.2 Factors Influencing Television Viewing Choice

As discussed in Chapter 1, we would like to incorporate several factors in an integrated television viewing choice model, including 1) programme characteristics; 2) past viewing behavior, and 3) family influence. Hence we separately examine literature related to these factors in the following.

2.2.1 Programme Characteristics

Programme characteristics are the dominant variable in most of the proprietary models that predict programme ratings (Gensch and Shaman, 1980). In previous studies, programmes were characterized either by using prior information (such as the Rust-Alpert categories) or by estimation based on observed viewing choices. The estimation method can be further divided into two approaches, factor analysis (Ehrenberg, 1968; Frank, Becknell and Clokey 1971; Gensch and Ranganathan, 1974; Swanson, 1967; Wells, 1969) or multidimensional scaling (Farley and Bowman, 1972; Lehmann, 1971; Rust, Kamakura and Alpert 1992). Thus there are three approaches to programme categorization: by using prior information, by estimation based on factor analysis, and by estimation based on multidimensional scaling.

The first approach establishes programme categorization based on prior information. In this approach, it is assumed that programme types can be judgmentally assigned, without reliance upon data. For example, Nielsen categorizes programmes into thirty types (e.g., drama, documentary, movie, etc.). Headen, Klompmaker and Rust (1979) and Rust and Alpert (1984) used a more concise categorization scheme which included five programme types: serial drama, action drama, talk, variety, and movie. This streamlined categorization scheme has been shown to improve the predictive power of television viewing models (Headen et al., 1979; Rust and Alpert, 1984).

The second approach uses factor analysis to classify programmes based on viewing choice data. Surprisingly, the results reveal that the derived categorization is similar to that from the first approach. For example, Gensch and Ranganathan (1974) found that programme categorization results were similar to the a priori categorization by Nielsen. Other researchers also obtained face valid categorization using factor analysis (Kirsch and Banks, 1962; Wells, 1969; and Frank, Becknell and Clokey 1971). However, Ehrenberg (1968) failed to discover meaningful programme types using this method. As in assignment of a priori programme types, the underlying assumption is that homogeneous programme categories do exist, in which similarity is defined largely by membership in the same category.

The third approach uses multidimensional scaling (or unfolding) technique to categorize programmes. This approach employs a continuous segmentation scheme and assigns programmes to different locations in an n-dimensional space, usually of low dimensionality, to facilitate interpretation. The distance between programmes in the space reflects programme similarity, based on which we can derive programme categorization. For example, Rust, Kamakura and Alpert (1992) used this approach to map cable television networks and viewers in the same space. Similarly, the derived programme categorization is similar to the first approach. In addition, Rust, Kamakura and Alpert (1992) found that programmes with similar content and programmes by the same channel tend to group together. For example, comedy programmes seem to split into two clusters, ABC comedy and NBC comedy.

Overall, the first approach is much easier than the other two, and the results are satisfactory in most of the research. It suggests that conventional, "common sense" programme types (such as drama, situation comedies, and so on) bear some systematic relationship to programme preference. In addition, the same type of programmes on different channels may have different utilities (Rosengren and Windahl, 1972; Owen et al., 1974). Hence we directly use the first approach and add the channel effect in our model in Chapter 3.

2.2.2 *Effects of Past Viewing Behavior*

Ehrenberg (1968) first proposed that prior viewing behavior is the key factor influencing current viewing choice. He argued that "the existence of different TV channels, of different times of the day, of different days of the week, and of different weeks… are already known – in a general sort of way – to affect viewing habits." This argument is supported by research findings in audience flow area where researchers address audience behaviors over time at the aggregate-level. According to prior research, audience flow normally has three characteristics: 1) repeat viewing, 2) inheritance effects, and 3) channel inheritance (Goodhardt et al., 1975; Krisch and Banks, 1962; Rao, 1975). Since audience flow is aggregation of individual viewing choice, characteristics of audience flow reveal the effect of past viewing behavior at individual level to some extent. We introduce the three characteristics one by one and propose the possible effect of past viewing behavior at individual level.

The first characteristic is repeat viewing, a predictable duplication of audience across a series of programmes (Goodhardt et al., 1975) . This can be seen in reports of how respondents get to a programme randomly selected from the previous day's viewing. Sixty-three percent had watched the programme before and knew it was going to be on. More than half (54 percent) said they almost always watched this programme. Earlier studies in the United Kingdom found the level of repeat viewing to be about 55 percent (Goodhardt, Ehrenberg and Collins 1980). The exception is daily soap operas, which average fairly consistently at about 10 percentage points higher (60-65 percent repeat-viewing). Many observers have noted the audience's apparent loyalty to daytime soap operas and the importance of a "continuing story" in generating this loyalty. Based on the characteristic of repeat viewing in audience flow, we propose that the individual-level past viewing behavior towards previous shows impacts future viewing intention towards a programme; we term this as "programme inheritance" in this paper.

The second characteristic is the lead-in effect, that is, a viewer's choice is also influenced by choice in the previous period (Goodhardt et al., 1975; Kirsch and Banks, 1962). On average, over 56% of a show's viewers watched the end of the previous show on the same network. This lead-in effect ranges from 32% to 81%, and it has a significant role in determining optimal network strategies (Goettler and Shachar, 2001). This effect is usually assumed to arise from cost of switching channels. Although it is often assumed that viewers constantly flip between channels, the facts are quite different. Viewers often persist in watching the same network for several sequential time slots. At individual level, it is termed as "state dependence", which means that the current choice behaviorally depends on the previous one (Moshkin and Shachar, 2002). There are several ways to explain viewing persistence, and one of them is switching cost. One distinct and salient feature of watching television (versus other leisure activities, such as social events, sports activities, or reading) is its passive nature – for many people, watching television is a way to relax. For these viewers, actively flipping channels might be annoying. Other viewers might face switching costs because they do not have a remote control or cannot find it. Moshkin and Shachar (2000) demonstrated empirically that state dependence is generated by switching costs for about half the viewers and by incomplete information and search costs for the remaining viewers.

The third characteristic, channel loyalty, is the tendency of programmes on the same channel to have a disproportionately large duplicated audience, a routinely observed feature of viewing behavior (Bruno, 1973; Darmon, 1976; Goodhardt et al., 1975; Rao, 1975). For example, most studies based on panel data have found that purchase of a brand increases the household's tendency to buy the same brand in the future (Keane, 1997; Gupta et al., 1997; Roy et al., 1996; Allenby and Lenk, 1995; Fader and Lattin, 1993). Moreover, consumer loyalty extends further than what is demonstrated by these studies. Aaker (1991) suggests that consumers can be expected to purchase different products from the same firm; Erdem (1998) and Anand and Shachar (2002) supported this view with panel data. Of course, the most striking features of loyalty appear in the television network industry. Despite the increase in the diversity of channels available since this study was conducted, this pattern still prevails. In a Times Mirror Center national survey (The Role of Technology in American Life, 1994), 61 percent said they usually turned in to see a specific programme that they knew will air at the time rather than dial around to see what might be on. A large majority (66 percent) said they don't switch channels frequently with their remotes as they watch television. Although almost every household in the United States has multiple channel choice, 65% of viewers have one majority watched channel (Shachar and Emerson, 2000). Based on the characteristic of channel loyalty, we propose that the past viewing behavior towards a channel will impact the future viewing intention towards this channel, which we term as "channel inheritance" in this current research.

To conclude, there are three components of the effect of past viewing behavior corresponding to the three characteristics of audience flow. However, among the three components, most previous research works incorporate only the "state dependence" (Rust, Kamakura and Alpert, 1992; Shachar and Emerson, 2000; Yang et al., 2010). Though the three components have been to improve rating prediction in audience flow research (Danaher 1991; Goodhardt and Ehrenberg 1969; Headen, Klompmaker, and Rust 1979), none of the above models incorporates the three components simultaneously. In the current research, we examine the three components simultaneously by allowing preference parameters to change dynamically over different series of the same drama (programme inheritance), over different timeslots of the same channel (state dependence), and over different days of viewing records for the same channel (channel inheritance).

---Insert Table 2.1 about here---

2.2.3 Family influence

The tendency of individuals to view in groups is a well-documented feature of audience behavior, particularly in prime time, which is quite often more of a family affair than a solitary activity (Bower, 1973). The data indicate that roughly two-thirds of prime-time viewing is done in the company of others – prime-time viewing is more likely to be a family affair rather than a solo activity (Clancey, 1994; and McDonough, 1993). Viewing television together is valued as one of the few evening activities in which families engage as it provides a relaxed, shared experience (Lee, 1986; Tichi, 1991).

Further, a number of studies have demonstrated that group viewing decisions affect individual choice in the selection of television programmes (see, for example, Lull, 1978; Lyle and Hoffman, 1973; Wand, 1968). The influence of groups appears to be another cause for the apparent randomness in individual programme choice. For example, Webster and Wakshlag (1982) demonstrated that individuals who view television programmes alone or in the same group generally have a greater tendency to watch programmes of a given type than those who view in groups of changing compositions.

Curiously, though interactions among family members during television viewing are likely to be significant because of cohabitation and strong emotional ties, most research in this area has been characterized historically by a preoccupation with viewers as individual decision makers. Most studies (except for Yang, Narayan and Assael, 2006; Yang et al., 2010) have ignored the potential interaction between different household members. They use individual viewers as the unit of analysis but do not examine viewing behavior of households as a unit.

There are two approaches to examine the family influence: stated or outcome-based. The stated approach uses measures such as a constant sum scale to assess influence (Corfman, 1989, 1991). Aribarg, Arora and Bodur (2002) used stated preference data to decompose member influence in groups' (parents and teenage children) decisions into two distinct elements of "preference revision" and preference concession". On the other hand, the outcome-based approach infers influence from data about individual preference of each consumer and from the outcome of a joint decision. Using conjoint analysis of data, Krishnamurthi (1988) proposed three models that combine individual preferences of MBA students and their spouses to approximate joint preferences and predict joint decisions. Arora and Allenby (1999) developed a hierarchical Bayesian model of group decision making that uses conjoint analysis of data and yields individual level estimates of influence at the product attribute level. Su et al. (2003) studied temporal effects in husband-wife decision making using conjoint analysis of data. Yang et al. (2006) demonstrated that individual programme preferences are interdependent between husband and wife and wife's preference depends more on husband's than husband's programme preference depending on wife's by using be Bayesian simultaneous equation model. Yang et al. (2010) propose a modeling framework to capture intra-household behavioral interaction based on family members' actual consumption behavior over time using a hierarchical Bayesian analysis.

In the current research, we don't have access to stated preference data; hence we infer family influence from the actual observed viewing behavior data. Specifically, we adapt Aribarg et al. (2002) and treat household television channel choice as the result of group decision making by household members and build a three-stage model to infer family influence during the decision process.

Next, we briefly review the related literature on group decision making.

2.3 Research on Group Decision Making

2.3.1 Decision Process

According to Aribarg, Arora and Bodur (2002), a general framework for group decisions can be divided into five sequential stages. In Stage 1 (pre-discussion), individual group members are assumed to have their own initial preferences. Then, group members are expected to engage in information exchange in Stage 2 (group discussion), in which they may make an effort to articulate their respective preferences and attempt to learn about others' preferences. Such a discussion may result in a change in each member's preference (Stage 3). At last, group members reach a joint decision or choice (Stage 4), and each member has a different level of satisfaction about the joint choice (Stage 5).

Though the above five-stage framework can be applied to most group decision making situations, modifications need to be made in this research due to two characteristics of household television viewing activities. First, we delete Stage 2 and Stage 3 to simplify the process of reaching the joint decision; and second, we add another step after the joint decision stage for individual family members to make individual final decisions. We discuss this in greater detail in Chapter 3.

2.3.2 Decision Rules

Several research studies have demonstrated that different household members have different decision powers and roles in the household decision process (Krishnamurthy, 1988; Atkinson, 1970). For example, Rigaux (1974) concluded that husbands and wives play different roles at various stages of the purchase decision making process. While characteristics of household decision structure of television viewing behavior are quantified with different theories like the cultural role expectation theory (Burgess and Locke, 1960), and the social power theory (French and Raven 1959) in behavioral literature, some alternative decision rules are defined by prior research on modeling group decision making.

We briefly review three group decision-making rules developed in the welfare economics literature that involve more than two group members. These rules differ in how group utility (preference) is formed based on individual group members' utilities (preferences). The first rule is called the Harsanyi solution proposed by Harsanyi (1955). In the Harsanyi group decision heuristic, group utility is a weighted average of individual group members' utility and the weights reflect members' relative influence in joint decision-making. The other two rules are referred to as the Maximum

Decision Heuristic (MAX) and the Minimum Decision Heuristic (MIN) proposed by Atkinson (1970). In MAX, group utility is formed based on the utility of the member who has the strongest preference among the family members. In MIN, group utility is formed based on the utility of the member who has the weakest preference among the family members.

Most previous studies on relative influence of individual members in a group decision context assume that groups adopt the Harsanyi decision rule (Krishnamurthy, 1988, Arora and Allenby, 1999, Aribarg, Arora and Bodur, 2002). Yang et al. (2010) also think the Harsanyi group decision heuristic is overall more likely to prevail than the MAX and MIN in joint consumption decisions (television viewing).

Hence we extend the Harsanyi decision rule to incorporate the varying decision powers of individual family members and interactions among family members in the current research.

CHAPTER 3 GROUP VIEWING MODEL (GVM)

In this chapter, we develop three sequential but interrelated sub-models (individual viewing preference sub-model, household viewing choice sub-model, and individual final response sub-model) to capture household's decision making procedure in television viewing. We use the maximum likelihood estimation to estimate the models via statistical inference of unobservable states. We conduct a simulation study to verify the methodology, and the results suggest that the true parameter values are recovered accurately and shares of predicted choices are almost identical to those of actual choices.

3.1 Overview of the Household Television Viewing Choice Decision Process

Based on the characteristics of television viewing, we review and compress the five stage framework of Aribarg, Arora and Bodur (2002) into three stages.

Television viewing is mainly a group activity. We can draw parallels from group decision making models for explaining the television viewing process. According to Aribarg, Arora and Bodur (2002), a general framework for group decision making can be divided into five sequential stages: pre-discussion, group discussion, change in preference, joint decision and evaluation (Figure 3.1). This framework allows us to describe household television viewing as follows. Initially, individual group members are assumed to possess their respective initial preferences in the pre-discussion stage (e.g., the father likes to watch football game on FOX while the daughter wants to watch a romantic drama on HBO). Group members are expected to engage in information exchange in the group discussion stage, when they may make an effort to articulate their individual preferences and attempt to learn about others' preferences (e.g., the father and the daughter voice their respective preferences). Such a discussion may result in a change in one or more member's preference (e.g., the father may decide to yield). The group members make a joint choice in the joint decision stage (e.g., the father and the daughter decide to watch the HBO channel together), and members evaluate their individual satisfaction levels towards the joint choice in the final stage.

---Insert Figure 3.1 about here---

Two characteristics of household television viewing activities are considered before we adapt Aribarg et al. (2002).

Firstly, television viewing normally needs minimal time and effort to reach a joint decision among family members, compared with many other household decisions (e.g., decisions about financial investments, family relocation, etc.). One possible reason is that television viewing is a frequently conducted leisure activity which doesn't involve consumption of economic and social resources. In addition, energy levels required are low and there are many distractions when family members watch television together, normally late in the day (Davis, 1976). Thus, we propose that family members reach their joint decision based on some decision rules without a formal group discussion (Stage 2 in Figure 3.1) or preference revision by individual members (Stage 3 in Figure 3.1).

Secondly, family members do not necessarily have to reach a decision acceptable to all members, unlike what is proposed in traditional group decision making literature.

Television viewing is an entertainment activity and after the discussion, members whose initial preferences are different from the joint decision can either revise their preferences and watch television together with other family members, or leave and choose not to watch television. We hence propose that family members need to make another decision (which is the final decision) after the household joint decision.

---Insert Figure 3.2 about here---

Figure 3.2 depicts the proposed household television viewing decision process after incorporating the two characteristics of household television viewing activities. It shows that household television viewing activity can be divided into three stages: 1) pre-decision stage, in which each family member has an initial channel preference (e.g., I would like to watch news on CNN); 2) joint-decision stage, in which family members make joint decisions based on some decision rules (e.g., the family has decided to watch a romantic drama on FOX) ; and 3) final-decision stage, in which individual family members respond to the joint channel choice, and make final decision (e.g., I decide not to join other members to watch the romantic drama on FOX).

To conclude, we simplify and reduce Aribarg et al's (2002) five-stage framework into three stages. This is consistent with former findings that the number of stages in the decision process is less in case of frequent activities (Davis, 1976). We propose that each family member is involved in three sequential and interrelated decisions during the television viewing decision process. Compared with the general framework of group decision making, the currently proposed framework is a simplified framework that reflects the essence of individuals' inputs and responses in the group decision process.

Please note that the above model is for households with one TV set. When there is more than one TV set in the household, family members have the option of watching another TV programme when a member's initial preference is different from the joint decision. Family members may split themselves into a number of sub-groups equal to the number of TV sets in the household, and then each sub-group makes a joint decision for each TV set. This is a logical extension of the proposed framework. Since most households (about 70% of households in panel data) have only one TV set (Nielsen, 2006), this research examines only households with one television set. It builds the foundation and allows future extension to households with more than one TV set. At last, though an increasing number of households now do have multiple sets available, television watching still occurs most often in a social context (McDonough, 1993).

Next, we use a sub-model to model each of the three stages. The dependent variables of the three sub-models are the three decisions viewers make during the decision process: individual preference, household viewing choice, and individual response to the household viewing choice.

3.1.1 Pre-Decision Stage: Individual Viewing Preference Sub-Model

In the pre-decision stage, each family member forms an individual viewing preference. As mentioned in Chapter 2, programme types and channels are the two most important factors influencing viewing utility. We first define a set of utility parameters denoting utilities of different channels (e.g., CNN, FOX) and different programme types (e.g., News, Cartoons) for each family member. Under a given schedule, we then compute each family member's utility towards a channel depending on the programme type scheduled on the channel (e.g., Father's utility towards watching news on CNN). We also define a constant utility to denote the 'not watching' utility for each family member. This leads to the pre-decision model, in which a channel with higher utility to the viewer is assumed to be chosen with higher probability. Thus, each member's viewing preference is a "choose one out of *n*" choice problem, with *n* being the number of viewing choices. The outcome of the pre-decision stage is individual viewing preferences. Figure 3.3 illustrates the process to model individual viewing preferences in the pre-decision stage.

---Insert Figure 3.3 about here---

3.1.2 Joint-decision Stage: Household Viewing Choice Sub-Model

In the second stage, the joint-decision stage, we derive household viewing choice based on individual viewing choices in the first stage. We separate the scenarios into two cases based on whether conflict exists among family members' individual viewing choices. If no conflict exists, then the household viewing choice is derived according to individual preferences. However, if conflict exists, we model how family members solve the conflict to reach the household viewing choice.

As aforementioned in Chapter 2, though there are several different models proposed to demonstrate the mechanism of interactions within groups (Choffray and Lilien, 1980), the most frequently used method to rationalize the joint decision is using analogy of a voting process called the Harsanyi decision rule. The Harsanyi decision rule suggests that the outcome of a group decision is a weighted function of group members' individual preferences, and the weights are determined by the relative influence of the members (i.e. each individual's influence over others). For example, if the household viewing choice is heavily influenced by the father, the father's choice should have the highest weight. In the current research, we extend the Harsanyi decision rule to incorporate the interactions among family members as well, and use second order weights to denote the coefficients of these interactions.

Hence we assume that in cases of conflict, family members vote according to their initial viewing preferences, and voting functions are built based on the extended Harsanyi decision rule to count the votes for different channels. The household viewing decision is derived by comparing values of voting functions.

To conclude, we model household viewing choice in the joint-decision stage from individual viewing choices in the pre-decision stage as illustrated in Figure 3.4. In consensus cases, household viewing choice is derived from individual viewing preferences. In conflicting situations, household viewing choice is derived from a voting process, and the Harsanyi decision rule is extended, in which both different levels of influence of different family members and interactions among family members are incorporated into the voting function.

---Insert Figure 3.4 about here---

3.1.3 Post-decision Stage: Individual Final Response Sub-Model

In the post-decision stage, family members respond to the joint decision, and make their final viewing choice. Even if the group can reach a joint decision, the joint decision may not satisfy all group members (Davis, 1976). Each family member in a one TV-set household has two options: watching television following the joint viewing choice, or not to watch at all. This decision is made by comparing the utility of watching the channel chosen by the joint decision and the utility of not watching TV at all. Figure 3.5 illustrates the process of the post-decision stage.

---Insert Figure 3.5 about here---

Till now, we have built individual viewing preferences sub-model for the pre-decision stage, a household joint viewing choice sub-model for the joint-decision stage, and an individual final response sub-model for the post-decision stage. Figure 3.6 graphically illustrates the linkages among the three sub-models. Individual viewing preferences sub-model is built first, based on utility parameters and programme schedule. Utility parameters are created specifically for different programme types and different channels. The household viewing choice sub-model is built by treating household television viewing as a voting process after formulation of the individual viewing preferences sub-model. The voting function incorporates different decision powers of family members and interactions between family members. Finally, the individual final response sub-model is built according to individual viewing preferences in the pre-decision stage and household viewing choice in the joint-decision stage.

---Insert Figure 3.6 about here---

Please note that the three-stage decision framework is built based on characteristics of household TV viewing choice. In most group decision making scenarios in prior literature, all group members need to reach consensus which means the only option each individual has is following the group decision in the response stage (Aribarg, Arora and Bodur, 2002; Davis, 1973; Su, Fern and Ye, 2003). For example, Aribarg et al. (2002) examined the probability of group members revising preferences or offering concessions in group decision making. However, group members have the option of revising preference only before making the group decision, and all group members have to concede to the joint decision even if there are conflicts between the revised preference and the joint decision. However, in the TV viewing choice scenario, family members may choose entertainment activities other than watching TV. Hence we provide another stage for family members to make another alternate decision, i.e. one may either watch television with other family members, or not watch at all. We believe that the current framework is nearer to real life situations and can be applied to many other scenarios.

Actually, the individual final response sub-model demonstrates the reciprocal effect in most of the traditional group decision making research. Most of the research in group decision area focuses on the role of members in group decision, that is, how individual members' choices influence group decision. The sub-model of the joint-decision stage uses this approach by demonstrating how individual viewing choices influence the joint household decision. For example, different individual members have different decision powers, and there are interactions among individual members on their respective viewing preferences. On the contrary, the individual final response sub-model for post-decision stage demonstrates the reciprocal effect; that is, how group decision can influence individual viewing choices. For example, the daughter may revise her viewing choice from CNN to HBO since the household joint viewing choice is HBO.

3.2 Model Formulation

Next, we illustrate mathematical representation of the above three sub-models.

3.2.1 Pre-decision Stage: Individual Viewing Preference Sub-model

Let subscripts *n*, *j*, *k*, and *t* denote family member *n*, programme type *j*, viewing choice *k*, and timeslot *t*. For the convenience of model presentation, let us assume a household *H* consists of three types of family members (*n* = f, m, c): father, mother, and child, whereas *f* stands for the father, *m* stands for the mother, and *c* stands for the child. Furthermore, there are only two television channels. After incorporating the choice of not watching, there are totally three viewing choices for each viewer (*k* = 0, 1, 2): not watching, watch channel 1 and watch channel 2.

Let $U_{nk(t)}$ be the utility of family member *n*'s viewing choice *k* at time *t*. When the family member chooses to watch television, $U_{nk(t)}$ would depend on programme type *j* aired on channel *k* (*k* = 1, 2). Let A_{njk} be family member *n*'s utility towards programme type *j* aired on channel *k*. Let $X_{jk(t)}$ be the television schedule, where $X_{jk(t)} = 1$ when programme type *j* airs on channel *k* at time *t*, otherwise $X_{jk(t)} = 0$. We can then derive a viewing option's utility towards a family member under the given schedule as follows:

$$U_{nk(t)} = \sum_j X_{jk(t)} * A_{njk} \qquad (k = 1, 2) \qquad (3.1a)$$

For example, if HBO is currently airing a romantic movie, the daughter's utility of watching channel one is her utility of watching a romantic movie on HBO, independent of the programme on the other channel and other household members' preferences. When a family member chooses not to watch, we define a constant θ_n as the utility of not watching for family member n. Family member n's utility is:

$$U_{nk(t)} = \theta_n \qquad (k = 0) \qquad (3.1b)$$

Utilities of different viewing choices directly drive the individual viewing preference sub-model, and indirectly drive the household joint viewing decision sub-model and the individual final response sub-model. Viewing choice with higher utility to the viewer is assumed to be more likely to be preferred. Thus, the viewer's viewing preference can be viewed as a multiple choice problem with three options: not watching, watching channel one and watching channel two. Let $C_{n(t)}$ be family member n's viewing decision at time t, where $C_{n(t)} = 1$ when family member n prefers channel 1 at time t, and $C_{n(t)} = 2$ when family member n prefers channel 2 at time t, and $C_{n(t)} = 0$ when family member n prefers not to watch at time t. The probability for family member n to prefer channel k at time t is derived according to the multinomial logit model (Lilien, Kotler and Moorthy, 2003):

$$P(C_{n(t)} = k) = \frac{e^{U_{nk(t)}}}{\sum_{k=0}^{2} e^{U_{nk(t)}}} \qquad (3.2)$$

For example, the father has the highest probability to prefer CNN channel, if the drama aired on CNN channel has the highest utility for the father among various viewing options.

3.2.2 *Joint-decision Stage: Household Viewing Choice Sub-model*

After each family member has an individual viewing preference in the pre-decision stage, the household collectively forms a household viewing choice in the joint-decision stage. To derive the household viewing choice, we treat the household decision making as a voting process. Family members first vote on each viewing choice based on their initial viewing preferences at the pre-decision stage. Let $V_{nk(t)}$ be the vote family member *n* gives to viewing choice *k* at time *t*, where $V_{nk(t)} = 1$ when member *n* prefers choice *k* at time *t*, and otherwise $V_{nk(t)} = 0$.

We separate the voting scenarios in the decision making process into two cases: consensus scenarios in which no conflict exists among family members (e.g., everyone prefers to watch the Discovery channel), and conflicting scenarios in which conflict exists (e.g., the father prefers to watch the FOX channel, and the mother and the daughter prefer to watch the HBO channel). We propose the following decision rules to model the decision process in both consensus and conflicting scenarios.

There are three possible scenarios: 1) at least one family member prefers channel 1 and the others prefer either the same channel or not watching; 2) at least one family member prefers channel 2 and the others prefer either the same channel or not watching; 3) all family members prefer not watching. In the first two scenarios, the household joint viewing choice is defined as the channel preferred by those who watch television (and they choose the same channel). The household joint channel choice is defined as not watching in the third scenario, since no one wants to watch at all. Let $G_{(t)}$ be the household joint viewing choice, where $G_{(t)} = 1$ when the household viewing choice is defined as channel 1, $G_{(t)} = 2$ when the household viewing choice is defined as channel 2, and $G_{(t)} = 0$ when the household viewing choice is not watching. Then,

$$\begin{aligned}
&P(G_{(t)} = 1 \mid V_{f1(t)} + V_{m1(t)} + V_{c1(t)} \neq 0, V_{f2(t)} + V_{m2(t)} + V_{c2(t)} = 0) = 1 \\
&P(G_{(t)} = 2 \mid V_{f1(t)} + V_{m1(t)} + V_{c1(t)} = 0, V_{f2(t)} + V_{m2(t)} + V_{c2(t)} \neq 0) = 1 \\
&P(G_{(t)} = 3 \mid V_{f1(t)} + V_{m1(t)} + V_{c1(t)} = 0, V_{f2(t)} + V_{m2(t)} + V_{c2(t)} = 0) = 1
\end{aligned} \tag{3.3}$$

In case of conflicting scenarios, while some family members choose channel 1, some other family members choose channel 2. To solve the conflict, we derive the household viewing choice by calculating the household's total votes for the two channels. In these conflicting scenarios, we assume that members choosing not to watch television do not participate in the voting process. Only those who prefer to watch television would cast a vote. Let ${}_gV_{k(t)}$ be household H's total votes for alternative channel k at time t, which can be specified by extending the weighted Harsanyi model (Atkinson, 1970; Yang et al., 2010) as follows.

$$\begin{aligned}
&{}_gV_{k(t)} \\
&= \sum_n \omega_n * V_{nk(t)} + \sum_{mn} \omega_{mn} * V_{nk(t)} * V_{mk(t)} \\
&= \omega_f * V_{fk(t)} + \omega_m * V_{mk(t)} + \omega_c * V_{ck(t)} + \\
&\omega_{fm} * V_{fk(t)} * V_{mk(t)} + \omega_{fc} * V_{fk(t)} * V_{ck(t)} + \omega_{mc} * V_{mk(t)} * V_{ck(t)}
\end{aligned} \qquad (k=1, 2) \quad (3.4)$$

In Equation (3.4), $V_{nk(t)}$ is defined as aggregation of each family member's weighted votes, and weighted multiplication of every two family members' votes. Weights ω_n are associated with other family members' respect towards family member n's viewing preference, or the insistence of family member n on his/her own preference; the larger the weight, the larger the family member's influence on the household viewing choice. A positive value of ω_n suggests that family member n's viewing preference is positively counted in forming the household viewing choice, that is, family member n's viewing preference is well-respected by other family members, or family member n strongly insists on his/her own preference. For example, in one family, father's viewing preference is always well-respected by other family members, or the father normally insists on his own preference, as reflected by a positive ω_f. Similarly, a negative ω_n suggests that family member n's viewing preference is negatively counted in forming the household viewing choice; that is, family member n's viewing preference is rejected by other family members, or family member n doesn't insist in his/her own preference. For example, son's viewing preference is sometimes rejected by father and mother since they want him to focus on his studies. Meanwhile, son doesn't insist on his own preference. The combination of the two factors leads to a negative ω_n. Finally, a zero value of ω_n suggests that family member n's viewing preference has no influence on the household viewing choice; that is, family member n's viewing preference is ignored by others, or family member n doesn't insist on his/her own preference. For example, if the daughter's choice is ignored, or if the daughter doesn't insist on her own preference, ω_d will be near zero.

The second order weights ω_{mn} are associated with interactions among any two family members. A positive value of ω_{mn} suggests a coalition effect between two members, that is, family member n and m tend to bargain together to have higher chances to watch their preferred channel. For example, the father and the mother may enjoy watching a romantic movie together, as reflected in a positive ω_{fm}. The father and the son may form an "alliance" to fight for a kung-fu drama, leading to a positive ω_{fd}. On the contrary, a negative ω_{mn} suggests a collision effect between two members, that is, family member n and m dislike watching television together so that their votes counteract when they choose the same channel. For example, the father and mother may have "collision" relationship since the mother always wants the father to wash dishes instead of watching television, and the father wants the mother to take care of the daughter's homework instead of watching television. Choice of television channel of the father and the mother may be consistently opposed to each other's preference. Another example is that the father may not enjoy watching adult programmes with her daughter around. Finally, a zero value of ω_{mn} suggests the behavioral interdependence between member n and m.

Therefore, the conditional probability of household joint viewing choice in the conflicting scenario can be derived according to logit model (Lilien, Kotler and Moorthy 2003):

$$P(G_{(t)} = k|_g V_{1(t)} \neq 0, {}_g V_{2(t)} \neq 0) = \frac{e^{{}_g V_{k(t)}}}{\sum_{k=1}^{2} e^{{}_g V_{k(t)}}} \tag{3.5}$$

For example, the household viewing choice has higher probability to be HBO channel, if the voting function for HBO channel has the highest value among other viewing choices. Note that Equation (5) indicates that the voting process would not end up as not watching (which is a "lose-lose" solution). Any member can always choose not watching if the household viewing choice is not of his or her preference. For example, the household viewing choice would not be not watching if father prefers to watch CNN channel and mother prefers to watch HBO channel.

3.2.3 Post-decision Stage: Individual Final Response Sub-model

After the family has made a joint viewing choice (i.e. which channel to watch together), each family member can respond to this joint viewing choice by joining or not joining the group to watch the chosen channel. Each family member's response is derived by considering both individual viewing preferences at pre-decision stage and household viewing choice at joint-decision stage. Let $R_{n(t)}$ be each family member's response, where $R_{n(t)} = 1$ when family member n finally views channel 1 at time t, $R_{n(t)} = 2$ when family member n finally views channel 2 at time t, and $R_{n(t)} = 0$ when family member n finally chooses not to watch at time t.

We classify the scenarios into two cases: consistent scenarios, where the family members' initial viewing choice is the same as the household viewing choice (e.g., both the daughter's individual viewing preference and the household viewing choice are the HBO channel), and inconsistent scenarios, where the two choices are different (e.g., the father's individual viewing preference is the FOX channel while the household viewing choice is the HBO channel).

For consistent scenarios ($C_{n(t)} = G_{n(t)}$), family member n's final response is the same as the household viewing decision. The conditional probability of family member n's decision, conditional on the consistency of initial viewing preference and household joint viewing decision, is:

$$P(R_{n(t)} = C_{n(t)} = G_{n(t)} \mid C_{n(t)} = G_{n(t)}) = 1 \qquad (3.6)$$

On the contrary, for inconsistent scenario ($C_{n(t)} \neq G_{n(t)}$), the family member can either follow the household viewing choice and watch together with other family members, or not watch at all. The individual final response is derived from comparison of the two options - option with higher utility is assumed to be more likely to be the individual final response. The utility of each option can be directly derived from (3.1a) and (3.1b).

Therefore, based on the above discussion, the conditional probability of family member n choosing to watch television together with other family members at time t, conditional on the inconsistency of initial viewing preference and household joint viewing choice is a logit model:

$$P(R_{n(t)} = k \mid C_{n(t)} \neq G_{n(t)}, G_{n(t)} = k) = \frac{e^{U_{nk(t)}}}{e^{U_{nk(t)}} + e^{U_{n0(t)}}} \qquad (k \neq 0) \qquad (3.7a)$$

Likewise, the conditional probability of family member n choosing not to watch television at time t, conditional on the inconsistency of initial viewing preference and household joint viewing choice, is:

$$P(R_{n(t)} = 0 \mid C_{n(t)} \neq G_{n(t)}, G_{n(t)} = k) = \frac{e^{U_{n0(t)}}}{e^{U_{nk(t)}} + e^{U_{n0(t)}}} \qquad (k \neq 0) \qquad (3.7b)$$

For example, when the daughter's individual viewing preference is the CNN channel and the household viewing choice is the HBO channel, the daughter can either watch HBO with other family members or choose not to watch. By comparing utilities of the two viewing choices, the daughter will choose to watch HBO channel if the utility of watching HBO channel is higher than that of not watching; otherwise the daughter will choose not to watch.

Last, across the two scenarios (consistent and inconsistent), the family member who prefers not to watch television in the pre-decision stage would still prefer not watching television at the post-decision stage. There are two underlying reasons for this: first, the family member who prefers not to watch television at time t may do so because he/she isn't at home at that time. The absence implies that the family member will still choose not to watch at the post-decision stage; secondly, when a family member prefers not to watch television in the pre-decision stage, the utility of not watching television should be the highest among the three viewing choices in both the pre-decision stage and the post-decision stage. Therefore, the family member will choose not to watch in post-decision stage.

$$P(R_{n(t)} = 0 \mid C_{n(t)} = 0) = 1 \qquad (3.8)$$

We have separated the household television viewing process into three stages (pre-decision stage, joint-decision stage and post-decision stage), and one sub-model (individual viewing preference sub-model, household viewing choice sub-model, and individual final response sub-model) is built for each stage. Altogether, there are three dependent variables: individual viewing preference ($C_{n(t)}$), household viewing choice

($G_{n(t)}$), and individual final response ($R_{n(t)}$). Among them, household viewing choice and individual final response are observed viewing records captured by the people meter system. However, the individual viewing preference is unobservable and needs to be inferred from family members' viewing records.

3.3 Estimation

3.3.1 Estimation Objective

There are two sets of parameters in the three sub-models, utility parameters (A_{njk}, k_n) and weighting parameters (ω_n, ω_{nm}). We estimate these parameters by fitting viewing records of each household with the proposed model.

Utility parameters allow us to understand the extent to which different types of programmes aired on different channels are favoured by each family member. By comparing utility parameters of different programmes, we can understand family members' programme preferences. By comparing utility parameters of different channels, we can understand family members' channel preferences. In addition, we can also segment preferences according to the parameters. If the viewer has strong programme type preference but weak channel preference, it indicates that the viewer is a "programme loyalist" whose viewing choice highly depends on the programme type aired on different channels. On the contrary, if the viewer has weak programme type preference but strong channel preference, it indicates that the viewer is a "channel loyalist" whose viewing choice highly depends on channel loyalty. The remaining viewers are somewhere in the middle, that is, their viewing choices are results of both programme type preference and channel loyalty.

The weighting parameters allow us to infer household decision making characteristics. Taking the first order weights as an example, we can define the family decision making mode from them. If family members have equal weights, then the household decision mode is democracy; if one family member's weight is much higher than others, then the household decision mode is autocracy (the family member with majority weight is the dictator). Meanwhile, we can understand the behavioral interactions among family members according to second order weights.

From the viewpoint of group decision making, we use an outcome-based approach for estimating group decision characteristics, i.e. we estimate utility parameters and weighting parameters according to the household viewing choice, and individual final response. Compared with the stated approach, which assesses group decision characteristics with questionnaires, outcome-based approaches are more accurate and objective (Corfman, 1989, 1991). Several researches have successfully used the outcome-based approach to estimate the group decision making structure. For example, using conjoint analysis of data, Krishnamurthi (1988) proposed three models that combine individual preferences of MBA students and their spouses to approximate joint preferences and predict joint decisions. Arora and Allenby (1999) developed a hierarchical Bayesian model of group decision making that uses conjoint analysis of data and yields individual-level estimates of influence at the product attribute level. Su et al. (2003) studied temporal effects in husband-wife decision making using conjoint analysis of data. Aribarg, Arora and Bodur (2002) used stated preference data to decompose member influence in a group (parents and teenage children) decision into two distinct elements of "preference revision" and "preference concession".

3.3.2 *Latent States Inference*

Each viewing record of a household indicates its viewing behavior on one viewing occasion, which includes the household viewing choice, and the individual final response of each family member. Since the individual viewing preference is unobservable in viewing records, these preferences can logically be assumed to have been induced by household viewing choice and individual final response.

As aforementioned, there are three options in each of the three decision stages. This results in a total of 27 (i.e. 3 x 3 x 3) unique combinations, or "latent states". Some of these latent states are logically impossible. For example, it is logically unsound for the father who prefers FOX over HBO to make an individual final response of watching HBO when the household viewing choice is FOX as well. Therefore, we outline four principles in our model building to highlight the impossible latent states:

1) *The consensus principle*: Equation (3.3) states that under consensus cases, the household viewing choice is reached with certainty based on simple comparison of votes for different viewing choices. The implication of this principle is that latent states under consensus cases, which lead to household viewing choices different from viewing records, are impossible.

2) *Household not watching principle*: Equation (3.5) indicates that the household viewing choice would never end up being 'not watching' when at least one family member prefers to watch television in the pre-decision stage. This principle implies that all family members' initial viewing preferences must be 'not watching,' when the household viewing choice is "not watching".

3) *The consistent principle:* Equation (3.6) states that under consistent cases, family members' final responses in the post-decision stage should the same as the initial viewing choice in the pre-decision stage. The implication of this principle is if the individual final response is different from the household viewing choice, it is logically unsound that a family member's viewing preference is consistent with the household viewing choice, and latent states containing such kind of individual preference are impossible.

4) *The individual not watching principle*: according to Equation (3.8), the family member who prefers not to watch television in the pre-decision stage would still prefer not watching television at the post-decision stage. The implication of this rule is that if the family member chooses to watch television at the final-decision stage (e.g., the father decides to watch the FOX channel with family members), then it is possible for him/her to prefer not watching in the pre-decision stage (e.g., it is impossible for father to prefer not watching television).

After assigning zero possibility to the impossible latent states, we can derive the likelihood function for each viewing record with reduced form. Next we use an example to illustrate the above process for inferring the latent states.

Example

Assume Table 3.1 is the viewing records for household *H* from time 1 to 3. We now illustrate inference of the impossible latent states given the viewing records at time 1, where the household, father, mother, and child's viewing choices are channel 1, channel 1, channel 1 and no-watch, respectively

($G_{(t-1)} = 1, C_{f(t-1)} = 1, C_{m(t-1)} = 1, C_{c(t-1)} = 0$).

---Insert Table 3.1 about here---

Table 3.2 lists the 27 latent states, and the conditional probabilities for household viewing records and family members' final responses, conditional on each latent state.

According to principle 1), $G = 1$ is impossible given the latent states of Nos. 8, 9, 11, 12, 13, 14 and 15. For example, the latent state of ($C_f = 2, C_m = 2, C_c = 2$) is the latent state of the consensus case, which leads to $G = 2$ instead of $G = 1$ in the joint-decision stage. Thus, we assign zero probability to these latent states.

Since the household watches television at time 1, principle 2) is not applicable here.

Next, according to principle 3), $R_c = 0$ is impossible given the latent states of Nos. 1, 3, 4, 7, 18, 20, 21, 25, and 27. For example, the individual viewing preference of ($C_c = 1$) is consistent with the household viewing choice ($G = 1$). However, since final response is ($R_d = 1$), the latent states containing this individual viewing preference are against decision rule 3).

Last, according to principle 4), $R_f = 1$ is impossibility given the latent states of Nos. 4, 6, 7, 11, 13, 14, 15, 24 and 25, and $R_m = 1$ is impossibility given the latent states of Nos. 3, 5, 7, 10, 12, 14, 15, 26 and 27. For example, the latent states of ($C_f = 0, C_m = 1, C_c = 1$) are impossible since ($C_f = 0$) in the pre-decision stage and ($R_f = 1$) in the post-decision stage is against decision rule 4).

As a result, there are six possible latent states of individual viewing preference for household *H* echoing the viewing record at timeslot 1 (Nos. 2, 16, 17, 19, 22, and

23), as highlighted in Table 3.2.

---Insert Table 3.2 about here---

To conclude, while the household decision making process happens sequentially in reality, from pre-decision to joint-decision and then to post-decision, we use backward induction to infer the latent states in the pre-decision stage given the observed household viewing choice and individual final responses. Following a similar logic, we can list all possible latent states in different viewing occasions for a three-member family and a four-member family.

3.3.3 Likelihood Function

After inferring the possible latent states echoing viewing records of household *H* at time *t* (including household viewing choice and individual final responses at time *t*), we are able to build joint likelihood function for household *H* during a certain time period *T*.

Let $H_{(t)}$ be household *H*'s viewing record at time *t*, and the probability of $H_{(t)}$ equals to the joint probability of household *H*'s viewing choice and family members' final responses (i.e. $P(H_{(t)}) = P(G_{(t)} = k_g, R_{f(t)} = k_f, R_{m(t)} = k_m, R_{c(t)} = k_c)$).

Assume there are *r* possible latent states echoing viewing records of household *H* at time *t*, and let $S_{i(t)} (i = 1,...,r)$ denote *r* possible latent states. The probability of viewing records $H_{(t)}$ conditional on latent state $S_{i(t)}$ equals to the joint probability of latent state $S_{i(t)}$, the conditional probability of household viewing choice $G_{(t)}$ conditional on latent state $S_{i(t)}$, and the conditional probability of individual final responses $R_{n(t)}$ conditional on latent state $S_{i(t)}$ and the household viewing choice $G_{(t)}$.

$$P(H_{(t)} \mid S_{i(t)}) = P(S_{i(t)}) * P(G_{(t)} = k_g \mid S_{i(t)}) * P(R_{f(t)} = k_f, R_{m(t)} = k_m, R_{c(t)} = k_c \mid S_{i(t)}, G_{(t)})$$

(3.9a)

After applying the three sequential and interrelated sub-models, the probability of viewing records conditional on each latent state equals to the joint probability of family members' individual viewing preferences in the pre-decision stage (i.e. the probability of one latent state), the household viewing choice in the joint-decision stage, and family members' final responses in the post-decision stage. Let $\pi^{i}_{nk(t)}$ be the probability of family member *n* choosing channel *k* at time *t* in the pre-decision stage under latent state $S_{i(t)}$, as defined by (3.2). Let ${}_{g}\pi^{i}_{k(t)}$ be the probability of household *H* choosing channel *k* at time *t* in the joint-decision stage under latent state $S_{i(t)}$, as defined by (3.3) and (3.5). Let ${}_{r}\pi^{i}_{nk(t)}$ be the probability of family member *n* choosing channel *k* at time *t* in the post-decision stage under latent state *i*, as defined by (3.6), (3.7a), (3.7b) and (3.8). After combining with (3.9a), the probability of household *H*'s viewing record at time *t* is derived as the function of $\pi^{i}_{nk(t)}$, ${}_{g}\pi^{i}_{k(t)}$ and ${}_{r}\pi^{i}_{nk(t)}$:

$$P(H_{(t)} \mid S_{i(t)}) = P(S_{i(t)}) * P(G_{(t)} = k_g \mid S_{i(t)}) * P(R_{f(t)} = k_f, R_{m(t)} = k_m, R_{c(t)} = k_c \mid S_{i(t)}, G_{(t)})$$

(3.9)

Where,

$$P(S_{i(t)}) = P(C_{f(t)} = k_f, C_{m(t)} = k_m, C_{c(t)} = k_c) = (\pi^{i}_{fk(t)}) * (\pi^{i}_{mk(t)}) * (\pi^{i}_{ck(t)})$$

$$P(G_{(t)} = k_g \mid S_{i(t)}) = ({}_{g}\pi^{i}_{k(t)})$$

$$P(R_{f(t)} = k_f, R_{m(t)} = k_m, R_{c(t)} = k_c \mid S_{i(t)}, G_{(t)}) = ({}_r\pi'_{fk(t)}) * ({}_r\pi'_{mk(t)}) * ({}_r\pi'_{dk(t)})$$

The probability of household H 's viewing records during the time period T is sum of the conditional probability of viewing record conditional on each latent state.

$$\begin{aligned}
P(H_{(t)}) &= \sum_{i=1}^{r} P(H_{(t)} \mid S_{i(t)}) \\
&= \sum_{i=1}^{r} P(S_{i(t)}) * P(G_{(t)} = k_g \mid S_{i(t)}) * P(R_{f(t)} = k_f, R_{m(t)} = k_m, R_{c(t)} = k_c \mid S_{i(t)}, G_{(t)}) \\
&= \sum_{i=1}^{r} (\pi'_{fk(t)} * \pi'_{mk(t)} * \pi'_{dk(t)}) * ({}_g\pi'_{k(t)}) * ({}_r\pi'_{fk(t)} * {}_r\pi'_{mk(t)} * {}_r\pi'_{dk(t)})
\end{aligned}$$

(3.10)

Finally, the probability of household H 's viewing records during the time period T is multiplication of the probability of viewing record at each time period.

$$P(H_T) = \prod_{t=1}^{T} P(H_{(t)}) = \prod_{t=1}^{T} \sum_{i=1}^{r} ((\pi'_{fk(t)} * \pi'_{mk(t)} * \pi'_{dk(t)}) * ({}_g\pi'_{k(t)}) * ({}_r\pi'_{fk(t)} * {}_r\pi'_{mk(t)} * {}_r\pi'_{dk(t)}))$$

(3.11a)

Since $\pi'_{nk(t)}$, ${}_g\pi'_{k(t)}$ and ${}_r\pi'_{nk(t)}$ are the function of utility parameters and weighting parameters according to (3.1)-(3.8), the joint likelihood of household H's viewing record can be derived as the function of these parameters. And we

$$P(H_T) = \prod_{t=1}^{T} P(H(t)) = \prod_{t=1}^{T} \sum_{i=1}^{r} (\pi'_{fk(t)} * \pi'_{mk(t)} * \pi'_{dk(t)}) * ({}_g\pi'_{k(t)}) * ({}_r\pi'_{fk(t)} * {}_r\pi'_{mk(t)} * {}_r\pi'_{dk(t)})$$

(3.11b)

To conclude, the joint likelihood function for each household is derived by multiplying the sum of all possible latent states for each viewing record. After building the likelihood function, we implement the model on the given viewing records of household H for a particular time period.

3.3.4 Implementation

The objective of implementation is to estimate the parameters by fitting the likelihood function into viewing records. We maximize the likelihood and select SAS-iml package as the analysis tool. During the estimation process, one important task is finding the starting points. Specifically, we use individual viewing records to find the starting points for utility parameters, household viewing records to find the starting points for weighting parameters, and then find the starting points for utility parameters and weighting parameters simultaneously. Appendix 2 illustrates the detailed process to find the starting points for utility parameters and weighting parameters. Appendix 3 illustrates a sample estimation programme.

Next, we apply the programmes on simulated data to evaluate the validity of the estimation process before applying it on real data.

3.4 Simulation

We now present a simulation study that demonstrates the validity of the proposed estimation procedure. Its performance under various conditions is examined experimentally.

3.4.1 Experiment Design

The experiment is a 3 (utility parameters: high differentiation, low differentiation and no-differentiation) x 3 (decision structures: democratic decision mode, autocratic decision mode and random decision mode) x 2 (sample size: small vs. large) factorial design. We replicate it five times in each condition.

In each condition, we assume that household H consists of three family members: father, mother and child (n=3). There are two television channels: channel 1 and channel 2, implying that each family member has three viewing options: channel 1, channel 2 and not watching. Programmes aired on the two channels are categorised into seven types (j=7). Parameters generated in each condition are listed as below.

Programme Schedule

Let $X_{jk(t)}$ be the programme schedule, where $X_{jk(t)} = 1$ when programme type j is aired on channel k at timeslot t, otherwise $X_{jk(t)} = 0$. The distribution of $X_{jk(t)}$ can be defined with $P(X_{jk(t)} = 1) = \frac{1}{j} = \frac{1}{7}$.

Utility Parameters

There are three conditions for utility parameters: 1) high differentiation between the utility of watching channel 1 and channel 2; 2) low differentiation between the utility of watching channel 1 and channel 2; 3) no differentiation between the utility of watching channel 1 and channel 2.

Let U_{njk} be the utility of programme type j aired on channel k for family member n. Under the high differentiation condition, U_{njk} is simulated as below:

Let X be a random number, simulated from $Uniform(0,1)$.

If $X \geq 0.5$, $U_{njk}(k=1) \sim Uniform(0,2)$ and $U_{njk}(k=2) \sim Uniform(8,10)$;

If $X < 0.5$, $U_{njk}(k=1) \sim Uniform(8,10)$ and $U_{njk}(k=2) \sim Uniform(0,2)$.

Under the low differentiation condition, U_{njk} is simulated as below:

Let X be a random number, simulated from $Uniform(0,1)$.

If $X \geq 0.5$, $U_{njk}(k=1) \sim Uniform(0,6)$ and $U_{njk}(k=2) \sim Uniform(4,10)$;

If $X \geq 0.5$, $U_{njk}(k=1) \sim Uniform(4,10)$ and $U_{njk}(k=2) \sim Uniform(0,6)$

Under the no differentiation condition, U_{njk} follows the prior distribution as below:

$U_{njk} \sim Uniform(0,10)$

Weighting Parameter

There are three conditions for the weighting parameters also: 1) democratic decision mode, in which family members' first order weights represent democratic decision mode, 2) autocratic decision mode, in which family members' first order weights represent autocratic decision mode; and 3) randomly generated, in which family members' first order weights are generated randomly. Across the three conditions, the second order weights are randomly generated.

Let ω_n be the first order weights for family member *n*. Under the democratic decision mode condition, we define that $\omega_f = 0.7$, $\omega_m = 0.2$, and $\omega_d = 0.1$.

Under the autocratic decision mode condition, we define that $\omega_f = 0.33$, $\omega_m = 0.33$, and $\omega_d = 0.33$.

Under the random generated condition, ω_n follows the prior distribution as below:

$\omega_n \sim Uniform(0,1)$

Sample Size

After generating the parameters, we simulate viewing records based on Equations (3.1) – (3.8). In order to examine whether sample size influences estimation, we simulate one sample comprising viewing records of 1,000 timeslots and another with records of 10,000 timeslots and compare the two.

3.4.2 *Simulation Process*

After generating programme schedule, utility parameters and weighting parameters, we simulate individual viewing choice, household viewing choice and individual final response. Individual viewing choice, household viewing choice and individual final response are simulated according to Equations (3.1)-(3.2), Equations (3.3)-(3.5), and Equations (3.6)-(3.8), respectively. Distributions of all three are binomial. Appendix 4 illustrates the detailed SAS code for simulation.

3.4.3 *Evaluation*

Till now, we have simulated viewing records under different conditions. Let $G_{(t)}$ be the simulated household viewing choice and $R_{n(t)}$ be the simulated individual final response. Next, we treat utility and weighting parameters as unknown and estimate them by using the proposed estimation procedure. During the process, only viewing choices and programme schedules are assumed to be observable. Let $\hat{U}_{njk}$ and $\hat{\omega}_n$ be estimated utility parameters and weighting parameters, respectively. The estimation procedure is validated by two criteria: hit rate, and the lift compared with the benchmark.

Hit Rate

Hit rate measures the absolute prediction rate, that is, the consistency between prediction and true value. Based on estimated utility parameters ($\hat{U}_{njk}$) and weighting parameters ($\hat{\omega}_n$), we predict viewing records according to Equations (3.1) – (3.8). Let $\hat{G}_{(t)}$ be the predicted household viewing choice and $\hat{R}_{n(t)}$ be the predicted individual final response. We can calculate the hit rate as below:

$$H_g = \frac{Count(G_{(t)} = \hat{G}_{(t)})}{Total} \tag{3.12a}$$

$$H_n = \frac{Count(R_{n(t)} = \hat{R}_{n(t)})}{Total} \tag{3.12b}$$

Lift

Lift represents the relative prediction accuracy rate by comparing the hit rate with the benchmark. In the simulation study, we use the highest possible hit rate as the benchmark. The highest possible hit rate is achieved when using true parameters (U_{njk} and ω_n) to derive the viewing records and accounting only the deterministic utility, without considering stochastic utility. Compared with hit rate, lift is a more objective criterion to evaluate estimation results across situations because it uses the highest possible hit rate any estimation can achieve. Let $G^B_{(t)}$ be the benchmark household viewing choice, calculated by using true parameters (U_{njk}), without stochastic utility. Let $R^B_{n(t)}$ be the benchmark individual final response, which is calculated using the true weighting parameters (ω_n), without stochastic utility. The benchmark hit rates can be calculated as below:

$$B_g = \frac{Count(G_{(t)} = G^B_{(t)})}{Total} \tag{3.13a}$$

$$B_n = \frac{Count(R_{n(t)} = R^B_{n(t)})}{Total} \tag{3.13b}$$

And the lifts are:

$$Lift_g = \frac{H_g}{B_g} \tag{3.14a}$$

$$Lift_n = \frac{H_n}{B_n} \tag{3.14b}$$

For example, if the hit rate is 40% and the benchmark is 80% at household level, then we can calculate the lift at household level as

$$Lift_g = \frac{40\%}{80\%} = 0.5$$

3.4.4 Simulation Results

Tables 3.3a and 3.3b illustrate the results for hit rate and lift, respectively; we can see that hit rates and lifts are high across different conditions. The average hit rate is 94% and the average lift is 0.93.

Specifically, differentiation among utility parameters impacts the estimation procedure. Hit rates and lifts are significantly higher under high differentiation conditions compared with low differentiation and no differentiation conditions. The average hit rate is 100% under high differentiation condition, 95% under low differentiation condition, and 78% under no differentiation condition. The average lift is 1.00 under high differentiation condition, 0.93 under low differentiation condition, and 0.90 under no differentiation condition.

The results also reveal that there are no significant differences in hit rates and lifts across different weighting parameters. The average lift is 92%, 95% and 92% under democratic decision, monarchy decision, and random decision mode, respectively. The average lift is 0.94 for democratic and monarchy decision modes, and 0.95 under the random decision mode.

Lastly, there are no significant differences in hit rates and lifts across different numbers of viewing records. The average hit rate is 91% for the small sample of 1000 records while it is 95% for the large sample with 10,000 records. Similarly, the average lift is 0.92 under the small sample and 0.97 under the large sample.

---Insert Tables 3.3a, 3.3b about here---

The results reveal that the model performs well under different conditions, which provides confidence for us to apply the model to real market data in later chapters.

CHAPTER 4 DYNAMIC GROUP VIEWING MODEL (DGVM)

Prior research indicates that viewing preferences may change with past viewing behaviors. In this chapter, we extend the group viewing model (Chapter 3) to incorporate effects of three past viewing behaviors: programme inheritance, state dependence and channel inheritance. The new model, termed as the dynamic group viewing model, allows us to examine the effect of household influence and past viewing behavior on individual viewing choice simultaneously.

4.1 Overview of the Dynamic Household Television Decision Process

The group viewing model (with three sub-models) in Chapter 3 treats household television viewing activity as a three-stage group decision making process. We first define a series of utility parameters to denote utilities of each family member's different viewing decisions. Under a given programme schedule, we can derive family members' individual viewing preferences, household viewing choice (by considering weighting parameters), and individual final responses. The process treats the utility parameters as static. However, prior research of audience flow indicates that individual utility parameters are not constant; they change dynamically with different past viewing behaviors.

Extant research on audience flow suggests that audience flow has three characteristics: 1) repeated viewing, which means a disproportionately high overlap of audiences across programmes in a series (Moshkin and Shachar, 2002; Tavakoli and Cave, 1996; Webster and Wakshlag, 1983); 2) lead-in effect, which means that viewers of one programme on a given channel will be disproportionately represented in audience for the following programme (Goettler and Shachar, 2001; Rust and Alpert, 1984; Webster, 1985); and 3) channel loyalty, which means a disproportionately high overlap of audiences across programmes aired on the same channel.

Since audience flow reflects individual viewing choice at the aggregate level, we conclude that past viewing behavior along the three dimensions would impact individual viewing preference. Specifically, the characteristic of repeated viewing indicates that the viewer's past viewing behavior towards a series programme will increase future viewing utility towards this programme, which we term as programme inheritance. Similarly, the characteristic of lead-in effect indicates that the viewer's past viewing behavior on prior timeslots of a day would increase viewing utilities at later timeslots of the same day, which is termed as state dependence in prior research (Goettler and Shachar, 1996; Moshkin and Shachar, 2002; Shachar and Emerson, 2000). The characteristic of channel loyalty indicates that the viewer's past viewing behavior on a channel would increase future viewing utility towards the same channel, which we term as channel inheritance.

To summarize, we define the past viewing behavior along three dimensions, i.e. programme dimension, timeslot dimension and channel dimension, which results in the three components of the effect of past viewing behavior, i.e. programme inheritance, state dependence, and channel inheritance. Hence, the dynamic group viewing model allows individual viewing utility to be influenced by the three components. We can study the effect of past viewing behaviors and family member influence simultaneously in the dynamic group viewing model.

In the group viewing model (Chapter 3), individual final responses are actual viewing behaviors of family members. Hence we can denote utility parameters as the function of past final responses along the three dimensions. Specifically, the utility of watching a certain channel at a certain timeslot for a family member would depend on the family member's past final responses towards the programme aired at the same timeslot, past final responses during prior timeslots on the same day, and past final responses towards the same channel.

Figure 4.1 depicts the framework of the dynamic group viewing model. We can see that utility parameters in the pre-decision stage are linked with past final responses in the post-decision stage. On one side, utility parameters drive the household viewing choice and individual final responses; on the other side, utility parameters are a function of prior final responses.

---Insert Figure 4.1 about here---

4.2 Model Formulation

To begin with, we derive the dynamic individual viewing utilities by incorporating the three effects of past final responses.

Consistent with those in the group viewing model, let subscripts n, j, q, k, and t denote family member n, programme q, programme type j, viewing choice k, and timeslot t, respectively. Any programme q belongs to a certain programme type j. For the convenience of model presentation, let us assume that household H consists of three types of family members ($n = a, b, c$), where a stands for the father, b stands for the mother, and c stands for the daughter. Furthermore, there are only two television channels. After incorporating the viewing choice of not-watching, there are totally three viewing choices for each viewer ($k = 0, 1, 2$), where 0 stands for not-watching, 1 stands for choosing channel 1, and 2 stands for choosing channel 2.

Let $A_{njk(t)}$ be the utility of programme type *j* aired on channel *k* at time *t* for family member *n*. Let $F_1[A_{njk(t)}]$ be the programme inheritance component determined by past final responses towards the programme. Let $F_2[A_{njk(t)}]$ be the state dependence component determined by past final responses towards prior timeslots on the same day. Let $F_3[A_{njk(t)}]$ be the channel inheritance component determined by past final responses towards the same channel. Then $A_{njk(t)}$ can be derived as the aggregation of $F_1[A_{njk(t)}]$, $F_2[A_{njk(t)}]$, and $F_3[A_{njk(t)}]$:

$$A_{njk(t)} = F_1[A_{njk(t)}] + F_2[A_{njk(t)}] + F_3[A_{njk(t)}] \tag{4.1}$$

4.2.1 Programme Inheritance: $F_1[A_{njk(t)}]$

Let us suppose programme *q* is aired on channel *k* at time *t*, and programme *q* is of type *j*. Since loyalty towards a programme can be formed only after viewers have watched the programme several times, we separate the dynamically changing pattern of the utility towards programme type *j* aired on channel *k* for family member *n* into two cases based on whether timeslot *t* is [among the first *d* times airing of programme *q* or not. (Since prime-time drama is launched once a day from Monday to Friday every week, *d* equals to five in the current research. This issue is discussed in Chapter 5.)

In the first case, when timeslot *t* is among the first *d* times' launch of programme *q*, we assume that programme utility is a constant. During this period, viewers are still at the stage of forming their preference towards the programme. Thus the effect of programme inheritance doesn't appear. Similar to the group viewing model, we define a series of parameters to denote utilities of different programme types aired on different channels. Let η_{njk} be the utility of watching programme q (of type j) aired on channel k for family member n, during the first d times airing of programme q, then $A_{njk(t)}$ equals to η_{njk} under this case.

In the second case, when timeslot t is not among the first d times airing of programme q, we assume the utility of programme q aired on channel k for family member n at time t is dynamically changed, which equals to a constant utility plus an additional utility related with the accumulative viewing records pertaining to programme q during its past several times of airing.

Let δ_{njk} be the constant utility of watching programme q of type j aired on channel k for family member n, after the first d times airing.

Let ${}_sS_{nq}$ be the past viewing record of family member n, where ${}_sS_{nq} = 1$ when family member n watches more than half of airings of programme q in the same timeslots during the s^{th} airing; otherwise ${}_sS_{nq} = 0$. ${}_sS_{nq}$ can be calculated from family member n's past final responses towards programme q. The accumulated past viewing of family member n can be denoted as $\frac{\sum_{s=1}^{d} {}_sS_{nq}}{d}$.

The total utility of watching programme q (of type j) aired on channel k for family member n under the second case is derived by adding the constant utility and the additional utility derived by accumulated past final responses.

Let D denote the two cases, where $D = 1$ when the programme on channel k is aired for the first d times at time t, that is, pre-launch period; otherwise $D = 0$. Then the utility of watching programme type j aired on channel k for family member n at time t contributed by programme inheritance can be denoted as:

$$F_1[A_{njk(t)}] = \eta_{njk} * D + (\delta_{njk} + \alpha_{njk} * \frac{\sum_{s=1}^{d} {}_s S_{nq}}{d}) * (1 - D) \tag{4.2}$$

4.2.2 State dependence: $F_2[A_{njk(t)}]$

The meaning of state dependence is that the current choice behaviorally depends on the previous one (Moshin and Shachar, 2002). We follow the methodology prevalent in prior research by creating various dummy variables for different flow states to study the effect of state dependence. The effects of different flow states are examined via a regression model (Goettler and Shachar, 2001; Moshkin and Shachar, 2002; Rust and Alpert, 1984; Rust, Kamakura and Alpert, 1992; Shachar and Emerson, 2000).

We define three types of timeslots: beginning timeslot, continuing timeslot and ending timeslot. A timeslot is a beginning timeslot if a programme is launched starting from this timeslot. A timeslot is a continuing timeslot if it is a continuation from the last timeslot. Finally, a timeslot is an ending timeslot when a programme ends at this timeslot.

In the model, we use two variables, $Begin_{k(t)}$ and $End_{k(t)}$, to indicate the timeslot type. Let $Begin_{k(t)}$ denote whether the timeslot is a beginning timeslot, where $Begin_{k(t)} = 1$ when timeslot *t* is the beginning timeslot for a certain programme on channel *k*, otherwise $Begin_{k(t)} = 0$. Let $End_{k(t)}$ denote whether the timeslot is an ending timeslot, where $End_{k(t)} = 1$ when timeslot *t* is the ending timeslot for a certain programme on channel *k*, otherwise $End_{k(t)} = 0$. Timeslot *t* is a continuing timeslot when both $Begin_{k(t)} = 0$ and $End_{k(t)} = 0$.

As listed in Table 4.1, there are four flow states' echoes to the three types of timeslots: 1) family member n watches channel k at timeslot (t-1), and timeslot (t-1) is the beginning timeslot; 2) family member n watches channel k at timeslot (t-1), and both timeslot (t-1) and timeslot t are continuing timeslots; 3) family member n watches channel k at timeslot (t-1), and timeslot t is the ending timeslot; 4) family member n watches channel k at timeslot (t-1), and timeslot (t-1) is the ending timeslot. We use the second flow state as the benchmark, and examine the effects of the other three flow states vis-à-vis the benchmark.

---Insert Table 4.1 about here---

Then $Begin_{k(t-1)} * C_{nk(t-1)}$, $End_{k(t)} * C_{nk(t-1)}$ and $End_{k(t-1)} * C_{nk(t-1)}$ represent the first, third, and fourth flow states, respectively, with respect to channel k for family member n. Specifically, $Begin_{k(t-1)} * C_{nk(t-1)}$ indicates the first flow state, where $Begin_{k(t-1)} * C_{nk(t-1)} = 1$ when family member n watches channel k at time (t-1) and (t-1) is the beginning timeslot of one specific programme; otherwise $Begin_{k(t-1)} * C_{nk(t-1)} = 0$. $End_{k(t)} * C_{nk(t-1)}$ indicates the third flow state, where $End_{k(t)} * C_{nk(t-1)} = 1$ when family member n watches channel k at time (t-1) and t is the ending timeslot of the programme; otherwise $End_{k(t)} * C_{nk(t-1)} = 0$. $End_{k(t-1)} * C_{nk(t-1)}$ indicates the fourth flow state, where $End_{k(t-1)} * C_{nk(t-1)} = 1$ when family member n watches channel k at time (t-1) and (t-1) is the ending timeslot of the programme; otherwise $End_{k(t-1)} * C_{nk(t-1)} = 0$.

Let ${}_1\beta_{nk}$ be the coefficient of the flow state of $Begin_{k(t-1)} * C_{nk(t-1)}$. ${}_1\beta_{nk}$ denotes the impact of the flow state on viewer n's utility when the viewer watches channel k at timeslot (t-1), and (t-1) is a beginning timeslot of a programme, compared with the impact when both timeslots t and (t-1) are continuing timeslots of the programme.

Let ${}_2\beta_{nk}$ be the coefficient of the flow state of $End_{k(t)} * C_{nk(t-1)}$. ${}_2\beta_{nk}$ denotes the impact of the flow state on viewer n's utility when the viewer watches channel k at timeslot (t-1), and t is an ending timeslot of a programme, compared with the impact when both timeslots t and (t-1) are the continuing timeslots of the programme.

Let ${}_3\beta_{nk}$ be the coefficient of the flow state of $End_{k(t-1)} * C_{nk(t-1)}$. ${}_3\beta_{nk}$ denotes the impact on viewer n's utility when the viewer watches channel k at timeslot (t-1), and (t-1) is an ending timeslot of a programme, compared with the impact when both timeslots t and (t-1) are continuing timeslots of the programme.

Then the utility of watching programme type j aired on channel k for family member n attributable to state dependence can be denoted as:

$$F_2[A_{njk(t)}] = \\ {}_1\beta_{nk} * Begin_{k(t-1)} * C_{nk(t-1)} + {}_2\beta_{nk} * End_{k(t)} * C_{nk(t-1)} + {}_3\beta_{nk} * End_{k(t-1)} * C_{nk(t-1)} \tag{4.3}$$

4.2.3 Channel Inheritance: $F_3[A_{njk(t)}]$

Let P_{nk} be the channel inheritance of family member n, where $P_{nk} = 1$ if channel k is the most frequently watched channel during the past week (i.e. viewer n watches channel k at more than half of the total timeslots when viewer n watches television), otherwise $P_{nk} = 0$. That is, P_{nk} is the function of family member n's past final response towards channel k.

Let γ_{nk} be the coefficient respective to family member n towards channel k. Then the utility of watching programme type j aired on channel k at time t attributable to channel inheritance can be denoted as:

$$F_3[A_{njk(t)}] = \gamma_{nk} * P_{nk} \tag{4.4}$$

At last, by integrating the three factors together, we can get the total utility for family member n to watch channel k at time t as:

$$\begin{aligned}
A_{njk(t)} &= F_1[A_{njk(t)}] + F_2[A_{njk(t)}] + F_3[A_{njk(t)}] \\
&= [U_{njk} * D + (\delta_{njk} + \alpha_{njk} * \frac{\sum_{s=1}^{d} {}_sS_{nq}}{d}) * (1 - D)] \\
&+ [{}_1\beta_{nk} * Begin_{k(t-1)} * C_{nk(t-1)} + {}_2\beta_{nk} * End_{k(t)} * C_{nk(t-1)} + {}_3\beta_{nk} * End_{k(t-1)} * C_{nk(t-1)}] \\
&+ [\gamma_{nk} * P_{nk}]
\end{aligned} \tag{4.5}$$

By putting (4.5) into other equations (3.1) – (3.8) in Chapter 3, we can get the dynamic group viewing model. The process for estimating the dynamic group viewing model is similar to the group viewing model presented in Chapter 3, except that utility parameters change dynamically with former final responses.

4.2 Model Implementation

While past viewing behavior has been recognized as one of the most important factors influencing viewing preference (Danaher and Mawhinney, 2001; Tavakoli and Cave, 1996), most of the literature focus on examining the influence of state dependence (Goettler and Shachar, 2001; Moshkin and Shachar, 2002; etc.). This chapter integrates the effect of programme inheritance, state dependence and channel inheritance together. Compared with previous research, the dynamic group viewing model integrates the three components simultaneously and provides richer information about viewing behaviors.

For example, by comparing η_{njk} and δ_{njk}, we can examine the pattern of dynamic change of utility parameters before and after the first d times airing. If δ_{njk} is higher than η_{njk} (for example, please give a life example), this suggests the utility towards programme type j on channel k for family member n increases after the pre-launch period. If δ_{njk} is lower than η_{njk}, utility towards programme type j on channel k for family member n decreases after the pre-launch phase. If δ_{njk} is similar with η_{njk}, utility remains the same after the pre-launch phase.

Meanwhile, since δ_{njk} indicates the average utility of programme type j aired on channel k for family member n, we can segment viewers based on the value of δ_{njk}, as in the group viewing model. By comparing δ_{njk} of different programmes, we can understand family member n's programme type preference. By comparing δ_{njk} of different channels, we can understand family member n's channel preference. If the viewer has strong programme type preference but weak channel preference, the viewer is a "programme loyalist" whose viewing choice highly depends on the programme type. On the contrary, if the viewer has weak programme type preference but strong channel preference, the viewer is a "channel loyalist" whose viewing choice highly depends on channel loyalty. The rest of viewers are somewhere in the middle, that is, their viewing choices are results of both programme type preference and channel loyalty.

We can also examine the influence of programme inheritance according to the value of α_{njk}. A higher positive value of α_{njk} indicates higher programme inheritance of programme type j aired on channel k for family member n.

Similarly, a higher positive value of ${}_1\beta_{nk}$ indicates higher state dependence when viewer n watches television on the last timeslot and the last timeslot is a beginning timeslot, compared with when both the last and current timeslots are continuing timeslots. A higher positive value of ${}_2\beta_{nk}$ indicates higher state dependence when viewer *n* watches television on the last timeslot and the current timeslot is an ending timeslot, compared with when both the last and current timeslots are continuing timeslots. A higher positive value of ${}_3\beta_{nk}$ indicates higher state dependence effect when viewer *n* watches television on the last timeslot and the last timeslot is an ending timeslot, compared with when both the last and current timeslots are continuing timeslots.

At last, γ_{nk} provides an indication of the channel inheritance effect. A higher positive value of γ_{nk} indicates higher channel inheritance effect for channel *k* for family member *n*.

We may also examine individual differences among variables. For example, prior studies indicate that the effect of past purchase behavior varies along different genders. They found that husbands and teenagers frequently bought new or different brands compared with wives (Davis, 1976). Wolff (1958) suggested that women, more than men, take a long time to make up their product and brand choices and are more stubborn about changing them. It would be worth studying whether a similar pattern exists for television viewing consumption. Thus, we can also link the parameters with demographic information to test individual differences along the parameters.

CHAPTER 5 MODEL APPLICATIONS

This chapter reports the process for applying the model on Hong Kong viewing records for year 2006. The analysis was conducted on viewing records of 140 households for primetime on weekdays. Besides, we also demonstrate how the parameter estimates provide significant managerial information on household decision structure, individual latent preference, and the influence of past viewing behavior for Hong Kong television industry by using a representative family. In addition, the model was verified by comparing its prediction accuracy with different benchmarks in training and validation samples.

5.1 The Data

5.1.1 Data Sources

The main dataset in the current research is Hong Kong viewing records for year 2006. In addition, we also acquire other data sources (including programme log and demographic information) to facilitate analysis.

Viewing Records

The main dataset is one year television viewing records collected by AC Nielsen from a sample of respondents, using People Meters, and made available by the Hong Kong Television Broadcasting Ltd. (HKTVB). The records document viewing behaviors of about 2,000 people in about 600 households, from 6 pm to 12 pm between January 2006 and December 2006. The variables in the dataset include each panel member's family ID and member ID, time and duration of each viewing occasion, and the watched channel. The raw dataset was restructured with the following steps before applying the model.

We first split the duration from 6 pm to 12 pm into 36 timeslots each of which lasts around 10-15 mins. We determine the starting and ending time of each timeslot based on programme schedules such that most timeslots contain only one programme. For example, we define 8:30 pm – 8:39 pm as the No. 15 timeslot. (Appendix 5 lists the starting and ending time of each timeslot in detail.). Next, we define viewing records in a timeslot as the viewing choice watched for major part of the timeslot. Based on this rule, we derive viewing records at household-level and for individual family members in each timeslot. Last, the whole viewing record dataset is split by household into sub-datasets.

Programme Log

The programme log we acquired contains programme schedules in year 2006 of two major television channels in Hong Kong: Television Broadcasts Ltd. (TVB) and Asia Television Ltd. (ATV). It records the name, and the starting and the ending time of each aired programme.

By combining the programme log with the restructured viewing records, we had a separate dataset for each household, with information for every timeslot in year 2006, when at least one member watched television; the type of programme watched, the channel watched, and watched by whom.

Demographic Information

We also acquired demographic information of the families and family members in the panel. The variables in the demographic dataset include family specific demographic variables (e.g., household income, number of children, education of the household head, geographic location, Internet access) and individual specific demographic variables (e.g., age, personal income and education).

Though there is no variable directly indicating the role of individual family members, we can infer a family member's role according to the demographic information. For example, if there are two males in the household and their age difference is higher than twenty and lower than fifty, we assume that the older male is the father and the younger male is the son. Based on similar rules, we derive the role of each member in the dataset.

5.1.2 Research Scope

Based on the market situation and the viewing records, we control our research scope as below.

Target Channels

In Hong Kong, there are four categories of television channels: 1) domestic free channels, 2) domestic pay channels, 3) non-domestic channels, and 4) other licensable channels. Among them, domestic free channels are very popular, and the penetration rate is close to 100% according to the Hong Kong Broadcasting Authority (www.hkba.hk/en/index.html). Compared with domestic free channels, the other three categories of channels are less pervasive and have less influence. The current license holders of domestic free channels are Television Broadcasts Ltd. (TVB) and Asia Television Ltd. (ATV), which together have almost 80% share in television audience in Hong Kong. We then focus on choices of TVB channel and ATV channel, and group the other channel choices together with not-watching-television as "no-watch". Thus, in the current research, the household as a whole or individual family members have only three viewing choices: TVB, ATV, and not watching.

We use the following rules to recode viewing records for each timeslot at household-level and for individual family members: the viewing choice in a timeslot is no-watch when the time of watching television is less than 50% of the total time of the timeslot, otherwise the viewing choice is watching either TVB or ATV. The viewing choice in a timeslot is TVB when the time of watching TVB is higher than 50% of the time of watching television in the timeslot, otherwise the viewing choice is ATV.

Time Range

We focus on viewing behaviors during prime-time on weeknights, which is between 8:00 pm and 10:30 pm from Monday to Friday, for several reasons. Firstly, television ratings of prime-time programmes usually involve the highest economic impact (Shachar and Emerson, 2000). Thus it is very important to understand the prime-time viewing behavior for better television rating prediction. Next, most family members are least likely to be at work, at school, or outside home during the prime-time on weeknights (Yang et al., 2010); thus the chances of non-availability are quite low. Thirdly, programme schedules on TVB and ATV are regular during prime-time, which means the impact of programme rescheduling can be ignored in the selected time range.

The descriptive statistics for programme log show that drama programmes account for 85% of the total timeslots during prime-time. Based on programme categorization by AC Nielsen, each drama in our data belongs to one of the following six categories: "Love" (romantic & love), "Comedy" (comedy), "Action" (action & kungfu), Cops (cops & detectives & horrors), "History" (history & ancient drama), and "Professional" (life of professionals). We group other programmes aired during the selected time range into a single category termed as "Others". Thus, we have a total of seven programme types in the analysis. Table 5.1 reports the percentage shares of timeslots and programmes included in each type.

---Insert Table 5.1 about here---

Household Range

In the panel data, parts of households seldom watch any of the television programmes; the number of timeslots where there is at least one member watching television is less than 10% of total timeslots. Such records were, therefore, excluded from the panel list. Families containing three or four members are the most prevalent and account for up to 66% of all families. We focus our analysis on 140 families with three or four family members, which have two parents and at least one child, and only one TV set.[1] Table 5.2 shows details of composition of the selected families. It shows that 55 families have two children, of which 14 have two daughters, 17 have two sons, and 24 have a daughter and a son. The reason of including two children families as well is to investigate the impact of family structure on family viewing decision making. As a result, we have 140 fathers, 140 mothers, 96 daughters and 99 sons in

[1]For households with multiple TV sets, we only observe whether each family member watches a program at time t, but we do not observe which group of family members watched the program together at time t. Nielsen Media Research didn't collect this information in year 2006.

the analysis.

---Insert Table 5.2 about here---

Table 5.3 reports variables' definitions and summary statistics of key demographics about the selected families and individual family members. Family specific demographic variables include household income, number of children, average education level of parents, working status of the mother, and Internet access. Individual specific demographic variables include the person's age.

---Insert Table 5.3 about here---

5.1.3 Implementation

To summarize, we focus on prime-time on weeknights from January 2006 to December 2006 and on the two most influential TV channels (TVB and ATV). We focus on data of 120 families comprising three or four family members. Based on the research scope, we have made the following modifications on Equation (4.5) before applying our model on viewing records.

Firstly, the utility for programme type "others" is defined without the component of "programme inheritance". In the current research, type "others" includes all non-drama programmes aired during prime-time on weeknights. Since programme inheritance isn't applicable for non-drama programmes, we discard the component of programme inheritance in utility for programme type "others". Let P denote whether the programme aired on timeslot t is drama or not; $P = 1$ when the programme aired is one of the six types of dramas, otherwise $P = 0$. Let ς_{nk} be the baseline utility for programme type "others" on channel *k* for family member *n*. The utility for family member *n* at timeslot *t* equals to ς_{nk} plus components of state dependence and channel inheritance when $P = 0$.

Secondly, we define the initial launch period as the first one week of airing of the programme. Since we focus on only weeknights prime-time, the initial launch period is the first five days and, therefore, we control for the effect of programme inheritance over the preceding five days only. Thus, "*d*" equals to five in Equation (4.5).

To summarize, Equation of (4.5) can be modified as:

$$
\begin{aligned}
A_{njk(t)} &= F_1[A_{njk(t)}] + F_2[A_{njk(t)}] + F_3[A_{njk(t)}] \\
&= [U_{njk} * D + (\delta_{njk} + \alpha_{njk} * \frac{\sum_{s=s-6}^{s-1} {}_s S_{nq}}{5}) * (1 - D)] * P + \zeta_{nk} * (1 - P) \\
&+ [{}_1\beta_{nk} * Begin_{k(t-1)} * C_{nk(t-1)} + {}_2\beta_{nk} * End_{k(t)} * C_{nk(t-1)} + {}_3\beta_{nk} * End_{k(t-1)} * C_{nk(t-1)}] \\
&+ [\gamma_{nk} * P_{nk}]
\end{aligned}
\tag{5.1}
$$

After sequentially applying the proposed model on sub-dataset for each household, we get parameter estimates for the household and its family members. Next, we discuss how the parameter estimates provide us with meaningful managerial information on household decision structure, individual latent preference, and the influence of past viewing behavior using a representative family from our analysis.

5.2 A Representative Family

We select household with ID number 10002016 as the representative family. We first illustrate the basic statistics of viewing records and demographic information.

5.2.1 *Basic Statistics*

Demographic information

As depicted in Table 5.4, the demographic information shows that household 10002016 is a four member family, comprising father, mother, daughter and son. This family has a slightly above average monthly income of US$5,000-$6,000. The father is 50 years old and the mother is 48 years old. They both have tertiary education and are working to earn a living. They have a 15-year-old daughter and a 12-year-old son. Their home has Internet access.

---Insert Table 5.4 about here---

Viewing Records

The summary statistics show that there were a total of 3,086 viewing occasions when at least one member watched television. The remaining 1,414 occasions are associated with no television watching.

Figure 5.1a plots the distribution of viewing occasions across the three viewing choices at household level, and for each family member. We can see that frequency distributions of the three viewing choices (TVB, ATV, not watching) are 50%, 34% and 16% at household-level, 36%, 24% and 40% for father, 38%, 32% and 30% for mother, 36%, 26% and 38% for daughter, and 28%, 18% and 54% for son. Figure 5.1b shows distribution of viewing occasions across the six types of programmes at household-level and for each family member. The frequency distribution for love, comedy, action, cops, history and professional is 21%, 11%, 17%, 18%, 12% and 21%, respectively, at household-level; 14%, 19%, 21%, 16%, 19% and 11% for father, 21%, 21%, 11%, 10%, 17% and 20% for mother, 25%, 19%, 10%, 10%, 17% and 19% for daughter, and 13%, 19%, 21%, 25%, 13% and 9% for son. The differences among the family viewing patterns and individual member's viewing patterns highlight the need for analyzing television viewing with a group decision making approach for one TV set families.

---Insert Figures 5.1a, Figure 5.1b about here---

5.2.2 Parameter Estimates

After applying the model on the sub-dataset for household 10002016, we can get the parameter estimates, including weighting parameter estimates which indicate the household decision structure, the initial and baseline utility estimates (which indicate individual latent preferences), and the dynamics estimates which indicate the effect of past viewing behavior.

We begin with discussion of weighting parameters' estimates, which include the first order weight estimates and the second order weight estimates.

5.2.2.1 Household Decision Structure

First Order Weights (ω_n)

As depicted in Table 5.5a, the first order weight estimates are 5.80 for father, 3.20 for mother, 0.24 for daughter, and -2.90 for son. As discussed in Chapter 3, one family member's first order weight is associated with other family members' respect towards this family member's viewing preference, where positive value indicates well-respected, negative value indicates rejection, and zero value indicates ignorance.[2] We can see that both the father and the mother's viewing preferences are well-respected by other family members, while the daughter's viewing preference is somewhat ignored by other family members, and the son's viewing preference is normally rejected by other family members.

Furthermore, we can infer the household decision mode by comparing the first order weights across different family members. Based on arbitrary judgment, we define that the household decision mode is autocratic when the highest first order weight is not less than twice the average value of the remaining first order weights; otherwise the household decision mode is democratic. Under the autocratic mode, the family member with the highest first order weight is the dictator in the family. We can see that the family decision mode is democratic and no family member is the dictator though the father has the highest first order weight.

---Insert Table 5.5a about here---

Second Order Weight (ω_{mn})

Table 5.5b shows the second order weights among any two family members, including 54.56 for father-mother dyad, -0.34 for father-daughter dyad, 9.93 for

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[2] In current analysis, we define the cutoff value for different parameter estimates as ± 1.00. That is, the parameter is significantly positive when its value is no less than 1.00; the parameter is significantly negative when its value is no higher than -1.00; and the parameter is non-significant when its value is within the range of ± 1.00.

father-son dyad, 33.21 for mother-daughter dyad, -11.09 for mother-son dyad, and -15.96 for daughter-son dyad. As discussed in Chapter 3, the second order weight is associated with the interaction between two family members. A positive value suggests a coalition relationship between the two family members, a negative value suggests a collision relationship, and zero value suggests behavioral interdependence. Based on the cutoff criterion in the current research, dyads of father-mother, father-son, and mother-daughter have coalition relationship during television viewing, dyads of father-daughter and daughter-son have collision relationship, and dyad of mother-son is behavioral interdependence on each other.

The second order weights also indicate some interesting findings which we discuss below.

Firstly, we can see that there are strong coalitions for dyads of father-son and mother-daughter. It is consistent with prior research on gender, in which gender has been found to be a dominant factor for studying parents-children relationships (Russell and Saebel, 1997; West and Zimmerman, 1987). According to the gender schema theory (Bem, 1985) or gender theory (West and Zimmerman, 1987), males and females behave differently on average, leading to a strong coalition relationship for dyads with the same gender.

We can also see that the absolute value for dyads of mother-daughter and mother-son are higher than dyads of father-daughter and father-son. Since the absolute value of first order weight indicates the strength of the interaction between the two family members, this result is consistent with traditional wisdom that normally mothers spend more time and interact more with children. The collision relationship of the dyad of mother-son is probably because the mother wants the son to focus on his homework.

Finally, the strong collision between the daughter and the son reflects the normal situation when there is more than one child of similar age in a household. Children with similar age often compete in leisure activities: they usually fight for toys, balls and the television remote controller. This phenomenon is more salient for the dyad of daughter-son due to their different gender roles, leading to the strong collision for the dyad of daughter-son during television viewing.

---Insert Table 5.5b about here---

5.2.2.2 Individual Latent Preference

Next, we discuss individual family members' own preferences. As discussed in Chapter 4, we have two sets of utilities: initial utility which denotes utilities during the initial launch (i.e. the first week of launch); and baseline utility which denotes the average individual utility after the initial launch (i.e. after the first week).

Baseline Utility (δ_{njk})

Table 5.6a lists individual family members' baseline utility estimates for different drama types aired on different channels. We can infer individual family members' latent preferences by directly comparing the baseline utility of different drama types on different channels.

As shown in Table 5.6a, the top three favorite drama types are comedy on TVB, action on TVB and history on ATV for father, comedy on TVB, love on TVB and professional on TVB for mother, love on TVB, professional on TVB and love on ATV for daughter, and cops on TVB, action on TVB and cops on ATV for son.

Comparisons among average baseline utility estimates of different channels indicate that the most favorite drama type is action for father, comedy for mother, love for daughter and cops for son. The results are consistent with the traditional wisdom that males (father, son) prefer dramas of masculine characteristics (action, cops), and females (mother, daughter) prefer dramas of feminine characteristics (love).

Comparisons among average baseline utilities of different channels indicate that dramas on TVB are more popular than those on ATV across the four family members. It is probably because of the high production quality of TVB dramas, which are normally self-produced by TVB and are akin to the real life of Hong Kong people. It is also consistent with the market situation that TVB is the current market leader in the Hong Kong television industry.

---Insert Table 5.6a about here---

Utility Difference (μ_{njk})

Table 5.6b lists individual family members' initial utility estimates for different drama types aired on different channels. By comparing the initial and baseline utility, we can examine the popularity trend of one type of drama on a channel. Let μ_{njk} be the difference between the baseline utility estimate and the initial utility estimate respective to programme type *j* aired on channel *k* for family member *n*. That is,

$$\mu_{njk} = \delta_{njk} - \eta_{njk} \tag{5.2}$$

Based on the cutoff criterion, positive utility difference indicates increased popularity of the drama, negative utility difference indicates decreased popularity of the drama, and insignificant utility difference indicates unchanged popularity of the drama.

Tables 5.6c lists individual family members' utility differences for different drama types aired on different channels.

We can see that most drama types are with increased popularity except for love on TVB, cops on ATV and history on ATV for father, action on TVB, love on ATV and professional on ATV for mother, action on TVB and comedy on ATV for daughter, and professional on TVB and love on ATV for son.

By comparing average utility differences for different drama types, we can see that the drama type with the highest increased popularity is action for father, comedy for mother, cops for daughter, and cops for son.

By comparing average utility differences for different channels, we can see that popularity of dramas on both TVB and ATV increases for the father, the daughter and the son. For mother, popularity of dramas on ATV decreases slightly after the first week.

---Insert Tables 5.6b and 5.6c about here---

5.2.2.3 The Effect of Past Viewing Behavior

We finally discuss dynamics estimates in individual family members' own utilities. Tables 5.7a – 5.7c list effects of past viewing behavior estimates for household 10002016.

Programme Inheritance (α_{njk})

As shown in Table 5.7a, programme inheritance is positive for most drama types across all family members. This indicates that each family member's own preference for one type of television programmes is positively related to viewing behavior towards the same type of television programmes during the last five times of airing. For the few situations in which programme inheritance has had a negative effect (i.e. love on TVB and professional on ATV for father, and history on TVB for daughter), the reason may be that the particular family member doesn't like such kind of programme.

Comparing across different family members, we can see that mother and daughter have higher programme inheritance than father and son. It is consistent with prior research that females normally have higher loyalty towards brands or watched shows. Comparing across different drama programmes, we can see that drama type love has the highest inheritance. Comparing across different channels, we can see that TVB dramas have higher programme inheritance than those on ATV.

---Insert Table 5.7a about here---

State Dependence (${}_1\beta_{nk}$, ${}_2\beta_{nk}$, ${}_3\beta_{nk}$)

We first compare average values of three state dependent coefficients. As shown in Table 5.7b, we can see that father, mother and daughter's state dependence varies across different states. We can see that there is a lower state dependence when a family member watches television on the last timeslot and the last timeslot is a beginning timeslot, compared with when both the last and the current timeslot are continuing timeslots. This is consistent with the market wisdom that viewers normally conduct a "trial viewing" and frequently switch between channels during the beginning stage of a television programme. The results also indicate a higher state dependence when family members watch television on the last timeslot and the current timeslot is an ending timeslot, compared with when both the last and the current timeslot are continuing timeslots. This demonstrates a normal market situation where there is a high switching cost when a drama approaches the ending. That is why some advertisers start to use this phenomenon by placing their advertisements near the end of a show. Finally, there is no significant state dependence effect when family members watch television on the last timeslot and the last timeslot is an ending timeslot, compared with when both the last and the current timeslot are continuing timeslots.

Again, comparing across different family members, the mother and the daughter have stronger state dependence than the father and the son for all the three types of state dependence effects. This indicates a gender effect consistent with that in programme inheritance. Comparing across different channels, dramas on TVB have higher state dependence than those on ATV for all the three types of state dependence effect.

---Insert Table 5.7b about here---

Channel Inheritance (γ_{nk})

Results for the component of channel inheritance are illustrated in Table 5.7c. When compared cross different family members, father and mother have higher channel inheritance that the daughter and the son. In addition, comparing across channels, channel inheritance is relatively higher on TVB than on ATV. This is consistent with the market situation that TVB is the market leader in Hong Kong television industry and attracts more viewers that ATV, especially in weeknights prime time.

---Insert Table 5.7c about here---

5.2.3 Prediction Rates

We use the Jackknife methodology, one of the cross validation methods outlined by Crask and Perreault (1977), to verify our results. We first give a brief introduction of the jackknife methodology.

The Jackknife Methodology

Cross validation is commonly used (Green and Tull 1978) for model verification. Usually, a researcher splits available observations into a training sample and a validation or hold-out sample. The training sample is used to estimate the parameters of the model. The resulting equations are then used to predict values of dependent variables for validation of the hold-out sample. Predicted values for the hold-out sample are compared with actual values in order to examine the predictive ability of the proposed model.

The Jackknife method is one of the cross-validation methods based on a rotating hold-out sample. A hold-out sample is usually a small sample since the purpose is to avoid problems associated with larger samples, i.e. the lack of uniqueness in jackknife estimates (Wildt et al., 1982).

In the current research, we first deleted data of some weeks with special events (i.e. Christmas in the week beginning 20 Dec, China New Year in the week beginning 12 Feb, etc.). After that, we conducted a rotated split sample, each containing only one week viewing records as the validation or hold-out sample. We first estimated the parameters with the training sample, and then calculated the channel choices based on the estimated parameters. By comparing the predicted choices with four sets of benchmarks, we can verify our model.

Benchmarks

We build four benchmarks to evaluate our prediction accuracy:

The first is basic benchmarks, calculated by only major viewership at household-level and individual family members; the second set of benchmarks is time-adjusted benchmarks, calculated by accounting for major viewership in each timeslot at household-level and for individual family members; the third set of benchmarks is drama-adjusted benchmarks, calculated by adjusting major viewership of each type of drama at household-level and for individual family members; and the fourth set of benchmarks is the prediction rate based on the individual viewing choice model without accounting for family members' influences.

Results

The jackknifed prediction rates are shown in Table 5.8a, and the lifts compared with different benchmarks are shown in Table 5.8b.

In the training sample, at household-level, the average lift is 2.31 compared with basic benchmarks, 1.93 compared with time-adjusted benchmarks, and 1.84 compared with drama-adjusted benchmarks. At individual level, the average lift is 2.13 compared with basic benchmarks, 1.87 compared with time-adjusted benchmarks, and 1.88 compared with drama-adjusted benchmarks.

In the validation sample, at household-level, the average lift is 1.81 compared with basic benchmarks, 1.59 compared with time-adjusted benchmarks, and 1.52 compared with drama-adjusted benchmarks. At individual level, the average lift is 1.78 compared with basic benchmarks, 1.48 compared with time-adjusted benchmarks, and 1.56 compared with drama-adjusted benchmarks. It shows that the prediction rate of our proposed model outperforms the four sets of benchmarks in terms of both training and validation sample.

---Insert Tables 5.8a, 5.8b about here---

CHAPTER 6 EMPIRICAL RESULTS

In this chapter, we examine whether household decision structure, family influence, and past viewing behavior vary across family members and families, and whether the heterogeneity can be explained on the basis of demographic characteristics of families and their members. We first classify the parameter estimates into categorical data, then conduct a series of stepwise logistic regressions by using the categorical data as dependent variables, and using the demographic variables as independent variables. The results have significant marketing and managerial implications.

6.1 Demographic Definitions

After sequentially applying the model on sub-datasets of different households, we obtain parameter estimates for different families, which are consolidated into one dataset. However, since the parameters are estimated from separate datasets, quantitative values of the parameters cannot be compared directly across households. Hence, the formerly quantitative parameter estimates are classified and recoded into categorical data. To see how demographics can help explain the parameter estimates, we conduct a series of analyses by regressing the categorical data on the demographic variables. To begin with, we introduce the demographic variables as below (Table 6.2).

Let $INCOME[1]$ and $INCOME[2]$ denote the household income level. $INCOME[1] = 1$ when the household monthly income is not less than HK$50,000, and $INCOME[1] = 0$ when the household monthly income is less than HK$50,000.

$INCOME[2] = 1$ when the household monthly income is not less than HK$20,000 and $INCOME[2] = 0$ when the household monthly income is less than HK$ 20,000.

Let EDU_P be the household education level, where $EDU\_P = 1$ when the household education level is not lower than secondary school/ Yijin, and $EDU\_P = 0$ when the household education level is lower than secondary school/ Yijin.

Let N_C be the number of children in the family, where $N\_C = 1$ when there are two children in the family, and $N\_C = 0$ when there is only one child in the family.

Let $WORK\_M$ be the mother's working status, where $WORK\_M = 1$ when the mother is a working-mom, and $WORK\_M = 0$ when the mother is a housewife.

Let $INTERNET$ be the Internet accessibility in the household, where $INTERNET = 1$ when there is Internet access at home, otherwise $INTERNET = 0$.

Let AGE_F be the age of the father in the household, AGE_M be the age of the mother in the household, AGE_C be the average age of children in the household (age of the child if there is only one child), AGE_D be the age of the daughter in the household, and AGE_S be the age of the son in the household.

---Insert Table 6.1 about here---

6.2 Household Decision Structure

As discussed in Chapter 1, we are interested in the household decision structure (e.g., what is the household decision mode, who is the dictator, and how are the interactions among family members), and how does it vary along different families and family members. We first classify the first order weights and second order weights estimates into categorical data, and then answer the above questions by conducting relevant analyses.

6.2.1 Household Decision Mode

a. Classification

We define household decision mode as autocracy if one family member's first order weight estimate is not less than two times the average first order weights of other family members, otherwise the household decision mode is democracy. Under autocracy, the family member with the highest first order weight is the dictator.

Let DM_H denote the decision mode of household *H*, where $DM_H = 1$ when the family decision mode is democracy (i.e. for all family members $\omega_i < 2 * \overline{\omega}_n$, $n \neq i$), and $DM_H = 0$ when the family decision mode is autocracy (i.e. $\omega_i \geq 2 * \overline{\omega}_n$, $n \neq i$). Let D_n denote the decision role of family member *n*, where $D_n = 1$ when family member *n* is the dictator (i.e. $\omega_i \geq 2 * \overline{\omega}_n$, $n \neq i$), otherwise $D_n = 0$.

Table 6.2a shows that 44% of households are democratic and the rest are autocratic. Among households who have an autocratic decision mode, father is the dictator in most households. It shows that 22% of households have father as the dictator, 16% of households have mother as the dictator, 8% of households have daughter as the dictator, and 10% of households have son as the dictator.

---Insert Table 6.2a about here---

b. Model Specification

In order to examine how the household decision mode varies along demographics of the family and family members, we conduct a series of stepwise binary logistic regressions using DM_H, D_n as dependent variables, and using demographic variables as independent variables.

$$P(DM_H = 1) = \frac{\exp(\beta_0 + \beta_1 * b_1 + \beta_2 * b_2 + ... + \beta_n * b_n)}{1 + \exp(\beta_0 + \beta_1 * b_1 + \beta_2 * b_2 + ... + \beta_n * b_n)}$$

$$P(D_n = 1) = \frac{\exp(\beta_0 + \beta_1 * b_1 + \beta_2 * b_2 + ... + \beta_n * b_n)}{1 + \exp(\beta_0 + \beta_1 * b_1 + \beta_2 * b_2 + ... + \beta_n * b_n)}$$

c. Results

We summarize the results in Table 6.2b, and highlight the major findings as below.

- The results of the stepwise logistic regression on DM_H show that

$$P(DM_H = 1) = \frac{EXP(0.53 + 0.67 * INCOME[1] + 0.26 * EDU\_P + 0.19 * N\_C)}{1 + EXP(0.53 + 0.67 * INCOME[1] + 0.26 * EDU\_P + 0.19 * N\_C)}$$

According to the model, the probability of democracy is positively related to *INCOME*[1] ($p<.05$), education level of parents ($p<.01$), and the number of children in the family ($p<.05$), and negatively related to the parents' education level ($p<.05$). It is independent of the rest of variables.

High-income families have higher likelihood of adopting the democratic decision mode, compared with low-income families. The underlying reason is probably that family members in high-income families usually have broader entertainment options, leading to a higher propensity to adopt a democratic decision mode.

The results also indicate that families with higher educated parents are more likely to adopt the democratic decision mode.

Finally, the results show that the family decision mode has higher propensity to be democratic when there are two children in the family. This is likely because when there are two children in the family, it is difficult for either to be the dictator.

- The results of the stepwise logistic regression on D_f show that

$$P(D_f = 1) = \frac{EXP(0.33 - 0.16 * EDU\_P - 0.78 * AGE\_C)}{1 + EXP(0.33 - 0.16 * EDU\_P - 0.78 * AGE\_C)}$$

According to the model, the probability for father to be the dictator is negatively related to parents' education level ($p<.05$) and the age of the children in the family ($p<.05$), and independent of the rest of variables.

We find that fathers in lower-education families tend to have a lower probability to be dictators. The results indicate that though adult males normally have dominant roles in Asian families, the trend decreases with increased education level of parents.

In addition, the probability for father to be the dictator decreases when the children grow up. This finding is consistent with the traditional wisdom that mothers spend more time in household chores and taking care of children when the children are young, leading to a stronger decision power of the father.

- The results of the stepwise logistic regression on D_m show that

$$P(D_m = 1) = \frac{EXP(0.26 + 0.69 * WORK\_M + 0.06 * INTERNET)}{1 + EXP(0.26 + 0.69 * WORK\_M + 0.06 * INTERNET)}$$

According to the model, the probability for mother to be the dictator is positively related to the working status of the mother ($p<.05$) and Internet accessibility ($p<.05$), and is independent of other variables.

We find that mother has higher propensity to be the dictator when she is a working-mom. According to the resource theory (Blood and Wolf, 1960) and the social power theory (French and Raven, 1959), relative income and education level are personal resources that help individuals gain more power. Current findings are consistent with this, that is, working-moms normally have more power in household decision-making, leading to a higher probability to be the dictator.

In addition, the results suggest that mothers have a higher probability to be the dictator in families with Internet access. This is likely because Internet can serve as an alternative entertainment for television viewing, and fathers or children are more easily attracted by it compared with mothers.

- The results of the stepwise logistic regression on D_d show that

$$P(D_d = 1) = \frac{EXP(0.17 - 0.23 * N\_C - 0.45 * INTERNET + 0.67 AGE\_D)}{1 + EXP(0.17 - 0.23 * N\_C - 0.45 * INTERNET + 0.67 AGE\_D)}$$

According to the model, the probability for daughters to be the dictator is negatively related to the number of children ($p<.05$) and Internet accessibility ($p<.05$), positively related to the age of the daughters ($p<.05$), and independent of the rest of variables.

The negative effect of the number of children in the family is consistent with former findings. That is, it is difficult for one of the children to be the dictator when there is more than one child in the family.

The results show that the probability for daughters to be the dictator increases with increased age of daughters, which is consistent with the traditional wisdom.

Finally, daughters have higher probability to be the dictator in families with Internet access than families without. This suggests that Internet is more attractive than television for young females.

- The results of the stepwise logistic regression on D_s show that

$$P(D_s = 1) = \frac{EXP(0.29 - 0.14 * N\_C - 0.09 * INTERNET)}{1 + EXP(0.29 - 0.14 * N\_C - 0.09 * INTERNET)}$$

According to the model, the probability for sons be the dictator is negatively related to the number of children ($p<.05$) and Internet accessibility ($p<.05$), and independent of other variables.

The findings are quite similar to those for daughters. That is, the propensity for sons to be the dictator is lower when there is Internet access in the family, and when the families comprise more than one child.

---Insert Table 6.2b about here---

6.2.2 Interactions between Family Members

a. Classification

We define interactions as coalition relationship, or collision relationship, or behavioral independence based on the cut-off value.[3] Let ω_{mn} denote the interactions between any two family members, where $\omega_{mn} = 1$ when the interaction

[3] We define the cutoff value as ± 1.00. That is, the interactions among family members are coalition when the respective second order weighting parameter estimates are no less than 1.00, the interactions among family members are collision when the respective second order weighting parameter estimates are no more than -1.00, and the family members are independence when the respective second order weighting parameter estimates are within the range of ± 1.00. We follow the same cutoff value for parameter estimates throughout current research.

between family member n and m is coalition, $\omega_{mn} = 2$ when the interaction between family member n and m is collision, and $\omega_{mn} = 0$ when the interaction between family member n and m is behavioral independence.

There are decision interactions for eight kinds of dyads; father-mother, father-daughter, mother-daughter, father-son, mother-son, daughter-daughter, daughter-son and son-son. As indicated in Table 6.3a the major interaction pattern is coalition for dyads of father-mother, mother-daughter, daughter-daughter and son-son, and it is collision for dyads of mother-son and daughter-son, while it is behavioral independence for dyads of father-daughter and father-son.

Comparison between dyads of the same gender (i.e. father-son, mother-daughter) and those of different genders (i.e. father-daughter, mother-son) reveals that interactions between family members of the same gender are more likely to be coalition compared with those between family members of different genders ($p<.01$). This is probably because males and females have different tastes towards television programmes, leading to a strong coalition relationship for dyads with the same gender ($p<.01$).

Comparison between dyads containing father (i.e. father-daughter, father-son) and those containing mother (i.e. mother-daughter, mother-son) reveals that mother-child interactions are higher than the father-child interactions ($p<.05$). This is consistent with the impression that mothers spend more time with children, leading to stronger behavioral interactions of mother-child dyads than father-child dyads.

---Insert Table 6.3a about here---

b. Model Specification

In order to examine how interactions among family members vary along demographics of the family and family members, we conduct a series of stepwise binary logistic regressions using ω_{mn} as dependent variables, and using demographic variables as independent variables.

$$P(\omega_{mn}=1)=\frac{\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}{1+\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}$$

$$P(\omega_{mn}=2)=\frac{\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}{1+\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}$$

c. *Results*

We then focus on how interactions of the six kinds of dyads (i.e. father-mother, father-daughter, father-son, mother-daughter, mother-son, and child-child)[4] vary along demographics of families and family members. We conduct a series of multinomial logistic regressions using ω_{mn} as dependent variable, and using demographics as independent variables.

- The results of the logistic regression on ω_{fm} show that

$$P(\omega_{fm}=1)=\frac{EXP(0.44+0.53*INCOME[1]+0.36*AGE\_C)}{1+EXP(0.44+0.53*INCOME[1]+0.36*AGE\_C)}$$

According to the model, the probability for interaction of father and mother to be positive is positively related to $INCOME[1]$ ($p<.01$) and the age of the children ($p<.01$), and is independent of the rest of variables.

The interaction between father and mother has higher propensity to be coalition

[4] Ideally, if there were more data available, one could estimate the model to separately account for daughter-son, daughter-daughter, son-son, father-daughter, father-son, mother-daughter, and mother-son. However, if we do so, we would significantly lose the statistical power due to a limited number of families we have for each type of family.

for high-income families than for low-income families.

In addition, their interaction tends to be coalition when the children in the family grow up. This is likely because parents are released from housekeeping and taking care of children when the children grow up.

$$P(\omega_{fm} = 2) = \frac{EXP(0.25 + 0.25 * N\_C - 0.41 * AGE\_C)}{1 + EXP(0.25 + 0.25 * N\_C - 0.41 * AGE\_C)}$$

According to the model, the probability for interaction of father and mother to be collision is positively related to the number of children (p<.05), negatively related to the age of children (p<.01), and independent of the rest of variables.

The interaction between father and mother has higher propensity to be collision when there are more children in the family, and when the children are young. This is consistent with previous findings that at least one parent needs to take care of the children when the children are young or when there are more than one children in the family, leading to the higher probability for father-mother interaction to be collision.

- The results of the logistic regression on ω_{fd} show that

$$P(\omega_{fd} = 1) = \frac{EXP(0.25 + 0.13 * EDU\_P - 0.22 * N\_C - 0.27 * AGE\_D)}{1 + EXP(0.25 + 0.13 * EDU\_P - 0.22 * N\_C - 0.27 * AGE\_D)}$$

According to the model, the probability for the interaction of father and daughter to be coalition is positively related to parents' education level (p<.01), negatively related to the number of children (p<.05) and age of daughter (p<.05), and independent of the rest of variables.

In other words, their interaction is more likely to be coalition for families with high education than low education, and less likely to be coalition for families having more than one child. The interaction between father and daughter is more likely to be coalition when the daughter grows up, which is consistent with the impression in real life.

$$P(\omega_{fd}=2)=\frac{EXP(0.37+0.46*INCOME[2]+0.05*AGE\_F)}{1+EXP(0.37+0.46*INCOME[2]+0.05*AGE\_F)}$$

According to the model, the probability for interaction of father and daughter to be collision is positively related to $INCOME[2]$ ($p<.05$) and the age of the father ($p<.05$), and independent of the rest of variables.

The results show that the probability for the interaction between father and daughter to be collision is lower for families with medium income than those with low income, and is higher when the father grows older.

- The results of the logistic regression on W_{fs} show that

$$P(\omega_{fs}=1)=\frac{EXP(0.33-0.14*N\_C-0.20*INTERNET)}{1+EXP(0.33-0.14*N\_C-0.20*INTERNET)}$$

According to the model, the probability for interaction of father and son to be coalition is negatively related to the number of children ($p<.05$) and Internet accessibility ($p<.01$), and independent of the rest of variables.

It shows that the interaction of father and son is less likely to be coalition when there is more than one child in the family, and when there is Internet access in the family. This result echoes the recent debate in the media on whether Internet reduces interactions among family members to some extent.

$$P(\omega_{fs}=2)=\frac{EXP(0.12+0.27*INCOME[2]-0.08*EDU\_P)}{1+EXP(0.12+0.27*INCOME[2]-0.08*EDU\_P)}$$

According to the model, the probability for interaction of father and son to be collision is positively related to $INCOME[2]$ ($p<.05$), negatively related to parents' education level ($p<.05$), and independent of the rest of variables.

In other words, the interaction between father and son is more likely to be collision for medium-income families than low-education families. This is likely because fathers from low education and low income families care for the son's studies more and give less freedom to the son for television viewing, leading to higher propensity for the interaction of father and son to be collision. The interaction is less likely to be collision for high-education families than low-education ones.

- The results of the logistic regression on ω_{md} show that

$$P(\omega_{md}=1)=\frac{EXP(0.17-0.11*WORK\_M-0.12*INTERNET)}{1+EXP(0.17-0.11*WORK\_M-0.12*INTERNET)}$$

According to the model, the probability for the interaction of mother and daughter to be coalition is negatively related to the work status of mother ($p<.01$) and Internet accessibility ($p<.05$), and independent of the rest of variables.

The interaction of mother and daughter is less likely to be coalition when the mother is a working-mom compared with when the mother is a housewife, which is likely because a working-mom is generally busier than a housewife.

$$P(\omega_{md}=2)=\frac{EXP(0.66+0.25*INCOME[1])}{1+EXP(0.66+0.25*INCOME[1])}$$

According to the model, the probability for the interaction of mother and daughter to be collision is positively related to income ($p<.05$), and independent of the rest of variables.

The interaction of mother and daughter is more likely to be collision for medium-income families than low-income ones. Similar to interaction of father and son, this result is likely because mothers in low-income families care more the daughter's studies and allow less freedom for the daughter to watch television, leading to the higher propensity for interaction of mother and daughter to be collision.

- The results of the logistic regression on ω_{ms} show that

$$P(\omega_{ms}=1)=\frac{EXP(0.39-0.26*N\_C-0.38*WORK\_M-0.09*AGE\_S)}{1+EXP(0.39-0.26*N\_C-0.38*WORK\_M-0.09*AGE\_S)}$$

According to the model, the probability for interaction of mother and son to be coalition is negatively related to the number of children ($p<.05$) in the family, working status of mother ($p<.01$), and age of the son ($p<.05$), and independent of the rest of variables.

The results reveal that interaction between mother and son is less likely to be coalition when the mother is a working-mom than when the mother is a housewife. This is consistent with the impression that working-moms normally spend less time with children.

It also shows that the interaction is less likely to be coalition when there are more children in the family, and when the son grows up.

$$P(\omega_{ms}=2)=\frac{EXP(0.61-0.22*EDU\_P+0.29*AGE\_M+0.16*AGE\_S)}{1+EXP(0.61-0.22*EDU\_P+0.29*AGE\_M+0.16*AGE\_S)}$$

According to the model, the probability for interaction of mother and son to be collision is positively related to age of the mother ($p<.05$), and age of the son ($p<.05$), negatively related to parents' education level ($p<.01$), and independent of the rest of variables.

The results also show that interaction between mother and son is more likely to be collision when the mother and the son grow older. The interaction also tends to be collision in families with higher-education level.

- The results of the logistic regression on ω_{cc} show that

$$P(\omega_{cc}=1)=\frac{EXP(0.48+0.35*N\_C)}{1+EXP(0.48+0.35*N\_C)}$$

According to the model, the probability for interaction of two children to be coalition is positively related to the number of children ($p<.01$), and independent of the rest of variables.

The results reveal that interaction between children is more likely to be coalition with increased age of children.

$$P(\omega_{cc}=2)=\frac{EXP(0.29-0.10*INTERNET)}{1+EXP(0.29-0.10*INTERNET)}$$

According to the model, the probability for interaction of two children to be collision is negatively related to Internet accessibility (p<.01), and independent of the rest of variables.

The interaction between children is less likely to be collision when the family has Internet access. It suggests that the Internet is an alternative entertainment for family members, leading to decreased competition for television among children.

---Insert Table 6.3b about here---

6.3 Individual Latent Preferences

Next, we discuss what determines an individual family member's own preference. As discussed in Chapter 1, we are interested in different aspects of individual latent preferences. For example, how individual family members' preferences vary across different types of dramas and channels? Can the heterogeneity be explained on the basis of demographic characteristics of families and family members? We classify individual baseline utility and initial utility estimates, and then answer the above questions by conducting relevant analyses.

6.3.1 Favorite Drama Type (FD_{njk})

a. Classification

We first define the favorite drama types on each channel for each family member. Let FD_{njk} indicate the favourability of different drama types, where

$FD_{njk} = 1$ $(j = 1,...,6)$ when the baseline utility of drama type *j* on channel *k* for family member *n* is the top-2 drama types among various baseline utilities of different drama types on channel *k*, otherwise $FD_{njk} = 0$.

Table 6.4a reports the descriptive statistics for FD_{njk}. Overall, drama types of "love" and "professional" are the most favorite drama types on TVB, and drama types of "history" and "comedy" are the most favorite drama types on ATV.

On TVB, drama types that are the top-2 with the highest frequency are comedy and action for father, love and comedy for mother, love and professional for daughter, and action and cops for son. On ATV, drama types that are the top-2 with the highest frequency are cops and history for father, love and comedy for mother, love and action for daughter, and action and cops for son. We can see that there are sharp distinctions between "things" that are masculine or feminine. As expected, both father and son like "action" more, and both mother and daughter like "love" more. These results reveal a great deal of apparent validity.

---Insert Tables 6.4a about here---

b. Model Specification

In order to examine how interactions among family members vary along demographics of the family and its members, we conduct a series of stepwise binary logistic regressions using FD_{njk} as dependent variables, and using demographic variables as independent variables.

$$P(FD_{njk}=1)=\frac{\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+\ldots+\beta_n*b_n)}{1+\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+\ldots+\beta_n*b_n)}$$

c. *Results*

In order to examine how latent preferences vary along different demographics, we conduct a series of binary logistic regressions using FD_{njk} as dependent variables, and demographic variables as independent variables. The results for FD_{njk} are listed in Table 6.4b; some interesting findings are highlighted herein below:

- Results of the logistic regression on FD_{njk} (k = TVB) show that:

For older fathers and those having more than one child, "comedy" has higher probability to be the top-2 drama type. "Cops" has low probability to be the top-2 drama type for fathers in high-income families, and "history" has high probability to be the top-2 drama type for fathers in high-education families.

For mother, "love" and "action" have higher probability to be the top-2 drama types when the children grow up. "Comedy" has higher probability to be the top-2 drama type for mothers in high-income families, and families with more than one child. "History" has higher probability to be the top-2 drama type for older mothers, and "professional" has higher probability to be the top-2 drama type for working-moms.

For daughter, "action" and "professional" have higher probability to be the top-2 drama types when she grows up. "Love" has lower propensity to be the top-2 drama type for daughters in families with Internet access. "Cops" has lower propensity to be the top-2 drama type for daughters in high-income families.

For son, "comedy" and "history" have lower probability to be the top-2 drama types when the family has Internet access. "Love" and "comedy" have lower probability to be the top-2 drama types for son when he grows up. "Action" and "cops" have lower probability to be the top-2 drama types for sons in high-income and high-education families.

- The results of the logistic regression on FD_{njk} (k = ATV) show that:

For favourability towards dramas on ATV, we find some similarity as well as differences in the impact of demographics compared to dramas on TVB.

Overall, as the number of children increases, we find an increased probability for "comedy" to be the top-2 drama type for father, mother and daughter. This is likely because "comedy" is the drama type normally watched by the household as a whole. It will have high popularity among bigger families (i.e. families with more children).

Both fathers and mothers tend to have a higher propensity to like "history" most in high-education families than in low-education ones.

---Insert Table 6.4b about here---

6.3.2 *Favorite Channel (FC_n)*

a. *Classification*

We now define the favorite channel for each family member. Let FC_n be family member n's favorite channel, where $FC_n = 1$ when family member n's average baseline utility for TVB dramas is not less than that for ATV dramas (i.e. $\bar{\delta}_{n(TVB)} \geq \bar{\delta}_{n(ATV)}$), otherwise $FC_n = 0$.

Table 6.5a reports the frequency distribution for favorite channel classification.

Overall, it indicates that TVB has higher propensity to be preferred than ATV across different family members. This is consistent with the market situation that TVB has a higher market share in weekday primetime than ATV due to its high quality dramas. As discussed in Chapter 5, while most dramas aired on TVB are self-produced by TVB, dramas aired on ATV are normally outsourced from foreign countries. Binary logistic regression further reveals that children have higher probability to prefer TVB than parents ($p<.05$). This is likely because dramas aired on ATV are normally produced in earlier years and are more attractive to older people, leading to higher propensity on part of parents to watch ATV.

---Insert Table 6.5a about here---

b. Model Specification

In order to examine how interactions vary along demographics, we conducted a series of binary logistic regressions using FC_n as dependent variables, and demographics as independent variables.

$$P(FC_n = 1) = \frac{\exp(\beta_0 + \beta_1 * b_1 + \beta_2 * b_2 + \ldots + \beta_n * b_n)}{1 + \exp(\beta_0 + \beta_1 * b_1 + \beta_2 * b_2 + \ldots + \beta_n * b_n)}$$

c. Results

Table 6.5b summarizes the results, and some interesting findings are highlighted herein below:

- Results of the logistic regression on FC_n show that:

The probability for TVB to be the favorite channel decreases for older fathers and older mothers.

For mother, the probability for TVB to be the favorite channel is lower for families with more children, for older mothers, and for working-moms (than housewives). This is likely because housewives have more leisure time than working-moms, leading to less selectivity for drama quality.

For daughter, the probability for TVB to be the favorite channel is lower in higher income families.

For son, the probability for TVB to be the favorite channel decreases when he grows up. In addition, the probability is lower for sons in families having Internet access. These results are likely because television viewing is a less attractive entertainment activity when the son grows up and when there is Internet access at home, leading to less selectivity for drama quality.

---Insert Table 6.5b about here---

6.3.3 *Popularity Trend (T_{njk})*

a. *Classification*

We define the popularity trend by comparing baseline utility and initial utility estimates. Let T_{njk} be the popularity trend, where $T_{njk} = 1$ ($j = 1,...,6$) when the baseline utility is not less than initial utility in respect of drama type j on channel k for family member n (i.e. $\delta_{nj} \geq \eta_{nj}$), otherwise $T_{njk} = 0$ (i.e. $\delta_{nj} < \eta_{nj}$).

b. *Results*

Table 6.6 summarizes the popularity trend classification.

Next we conduct a series of binary logistic regressions using T_{njk} as dependent variables, and drama type as independent variable. The results reveal that "professional", "love", and "cops" have higher probability to have increasing popularity trend, and "comedy", "history", "action" and "comedy" have lower probability to have decreasing popularity trend.

The binary logistic regression using T_{njk} as dependent variable and the channel as independent variable reveals that dramas on TVB have higher probability to have increasing popularity trend than those on ATV ($p<.05$).

Last, we conduct binary logistic regression using T_{njk} as dependent variable, and the gender as independent variable. The results reveal that the probability for having increasing popularity trend is higher for females (i.e. mother and daughter) than males (i.e. father and son). This is consistent with the gender effect mentioned in Chapter 5.

---Insert Table 6.6 about here---

6.4 The Influence of Past Viewing History

As discussed in Chapter 1, we are interested in the dynamic change pattern; for example, influence of past viewing behavior on different family members, and variation in effects across families, and whether the heterogeneity can be explained on the basis of demographic characteristics of families and family members. After defining classification based on dynamic estimates, we answer the above questions by conducting relevant analyses of the classification.

6.4.1 Programme Inheritance (PI_{njk})

a. Classification

We define programme inheritance as positive, zero or negative based on parameter estimates (α_{njk}). Let PI_{njk} be the programme inheritance for drama type j on channel k for family member n, where $PI_{njk} = 1$ when programme inheritance is positive, otherwise $PI_{njk} = 0$.

As indicated in Table 6.7a, programme inheritance has positive effect on later viewing intentions in most situations.

We first conduct binary logistic regression using PI_{njk} as dependent variables, and the channel as independent variable. The result indicates that dramas on TVB have higher probability to have positive programme inheritance than those on ATV ($p<.05$).

We next conduct a series of binary logistic regressions using PI_{njk} as dependent variables, and drama type as independent variable. The results reveal that "professional", "love" and "cops" have higher probability to have positive programme inheritance, and "comedy", "history", "action" and "comedy" have less probability to have positive programme inheritance.

Last, we conduct binary logistic regression using PI_{njk} as dependent variables, and the member role as independent variable. The results reveal that the probability of having positive programme inheritance is higher for mother and daughter than for father and son.

---Insert Table 6.7a about here---

b. Model Specification

In order to examine how programme inheritance varies along demographic information, we conducted a series of multinomial logistic regressions using PI_{njk} as dependent variables, and demographic variables as independent variables.

$$P(PI_{njk}=1)=\frac{\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}{1+\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}$$

c. *Results*

Table 6.7b reveals how individuals' programme inheritance varies across demographics; major findings are:

- Results of the logistic regression on PI_{njk} ($k=$ TVB):

For father, programme inheritance on TVB has lower propensity to be positive in case of high-income family than in low-income family. This is probably because people with high incomes normally have less leisure time leading to lower programme inheritance. Also, programme inheritance has lower propensity to be positive for fathers in families with Internet-access. This is consistent with market norms that Internet access provides an alternative entertainment besides television, leading to lower programme inheritance.

For mother, programme inheritance on TVB has lower propensity to be positive in case of two-child families than one-child families.

For daughter, programme inheritance on TVB has lower probability to be positive in case of high education families than low education families.

For son, programme inheritance on TVB has lower probability to be positive in case of families with Internet access than families without Internet.

- Results of the logistic regression on PI_{njk} ($k=$ ATV):

Programme inheritance towards dramas on ATV has similarity as well as differences in terms of impact of demographics compared to dramas on TVB.

For father, programme inheritance on ATV has lower propensity to be positive for high income families than low income families. Also, programme inheritance has higher propensity to be positive for older fathers, and when the mother is a housewife.

For mother, programme inheritance on ATV has lower propensity to be positive in case of working-moms, and mothers in two-child families compared with one-child families and mothers in families with younger children. This is consistent with the traditional wisdom that mothers normally have less leisure time when they are working moms, and when the children are young, leading to lower programme inheritance.

For daughter, programme inheritance on ATV has lower probability to be positive in case of high and medium income families than low-income families. Programme inheritance has lower probability to be positive for daughters in families with Internet access than in families without Internet access.

Similar to daughter, programme inheritance on ATV has lower probability to be positive for sons in families with Internet access than families without Internet. In addition, the probability decreases when the son grows up, and when the family has high income compared with families having medium income.

---Insert Table 6.7b about here---

6.4.2 *State Dependence* $({}_1SD_{nk}, {}_2SD_{nk}, {}_3SD_{nk})$

a. *Classification*

Based on state dependence estimates, we define classification to indicate family members' state dependence. Let ${}_1SD_{nk}$ be the state dependence when family member

n watches channel k at the last timeslot, and the last timeslot is the beginning timeslot, where ${}_1SD_{nk} = 1$ when the state dependence coefficient is positive respective to channel k and family member n, otherwise ${}_1SD_{nk} = 0$. Let ${}_2SD_{nk}$ be the state dependence when family member n watches channel k at the last timeslot, and the current timeslot is the ending timeslot, where ${}_2SD_{nk} = 1$ when the state dependence coefficient is positive respective to channel k and family member n, otherwise ${}_2SD_{nk} = 0$. Let ${}_3SD_{nk}$ be the state dependence when family member n watches channel k at the last timeslot, and the last timeslot is the ending timeslot, where ${}_3SD_{nk} = 1$ when the state dependence coefficient is positive respective to channel k and family member n, otherwise ${}_3SD_{nk} = 0$.

Table 6.8a shows descriptive statistics of state dependence classification.

Compared across the three types of state dependence, the second state dependence has the highest probability to be positive, while the third state dependence has the lowest probability to be positive.

State dependence has higher propensity to be positive on TVB than on ATV across all the three types (of state dependence).

Comparing across different family members, we can see that the first state dependence has the highest probability to be positive for father, and has the lowest probability to be positive for daughter. The second state dependence has the highest probability to be positive for son, and the lowest probability to be positive for mother. The third state dependence has the highest probability to be positive for mother, and the lowest probability to be positive for father.

---Insert Table 6.8a about here---

b. Model Specification

In order to examine how programme inheritance varies along demographic information, we conducted a series of multinomial logistic regressions using ($_1SD_{nk}$, $_2SD_{nk}$, $_3SD_{nk}$) as dependent variables, and demographic variables as independent variables. In each multinomial logistic regression, we use behavioral independence as the benchmark condition.

$$P(_1SD_{nk}=1)=\frac{\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}{1+\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}$$

$$P(_2SD_{nk}=1)=\frac{\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}{1+\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}$$

$$P(_3SD_{nk}=1)=\frac{\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}{1+\exp(\beta_0+\beta_1*b_1+\beta_2*b_2+...+\beta_n*b_n)}$$

c. Results

Table 6.8b reveals many interesting findings on how individuals' programme inheritance varies across families and individuals.

- Results of logistic regression on $_1SD_{nk}$ show that:

The first state dependence has lower propensity to be positive for fathers in high-income families than in low-income families. This is probably because people with high incomes normally have less leisure time leading to higher switching propensity at the beginning of each programme.

The first state dependence has higher propensity to be positive for mothers in families with older children.

The first state dependence has lower propensity to be positive for sons in Internet-access families.

- Results of logistic regression on ${}_2SD_{nk}$ show that:

The second state dependence has higher propensity to be positive for fathers in families with older children, and older fathers.

Also, the second state dependence has higher propensity to be positive for older mothers and has lower propensity to be positive for working moms.

The second state dependence has lower propensity to be positive for sons in medium-income families than low-income families.

- Results of logistic regression on ${}_3SD_{nk}$ show that:

The third state dependence has lower propensity to be positive for fathers in high-income families than low income families, and has higher propensity to be positive for older fathers.

The third state dependence has lower propensity to be positive for working moms, and for mothers in high education families than low education families. It is probably because mothers in high education families are more involved in entertainment activities (e.g., reading, playing with children) other than watching television. At last, the third state dependence has higher propensity to be positive for mothers in families with older children.

The third state dependence has lower propensity to be positive for daughters in high education families than low education families, and for daughters in families with Internet access.

---Insert Table 6.8b about here---

6.4.3 Channel Inheritance (CI_{nk})

a. Classification

Based on programme inheritance estimates, we define classification to indicate family members' channel inheritance. Let CI_{nk} be the channel inheritance respective to channel *k* for family member *n*, where $CI_{nk} = 1$ when channel inheritance is positive, otherwise $CI_{nk} = 0$.

Table 6.9a shows that channel inheritance has higher propensity to be positive for TVB than for ATV. Comparisons across different family members reveal that channel inheritance has the highest probability to be positive for father, and has the lowest probability to be positive for son.

---Insert Table 6.9a about here---

b. Model Specification

In order to examine how channel inheritance varies along demographics, we conducted a series of binary logistic regression using CI_{nk} as dependent variables, and demographic variables as independent variables.

$$P(CI_n = 1) = \frac{\exp(\beta_0 + \beta_1 * b_1 + \beta_2 * b_2 + ... + \beta_n * b_n)}{1 + \exp(\beta_0 + \beta_1 * b_1 + \beta_2 * b_2 + ... + \beta_n * b_n)}$$

c. Results

Table 6.9b reveals the major findings on how individuals' programme inheritance varies across families and individuals.

- Results of the logistic regression on CI_{nk} show that

Channel inheritance has lower propensity to be positive for older fathers and mothers. This is probably because older fathers and mothers normally have more leisure time, leading to higher channel inheritance.

Channel inheritance has lower propensity to be positive for working moms than housewives. This is likely because working moms have more [less?] leisure time, leading to lower channel inheritance.

Channel inheritance has lower propensity to be positive for sons in families with Internet access.

---Insert Table 6.9b about here---

6.5 Key Findings Summary

The integrated results have important marketing and managerial implications. Specifically, the results indicate the main influencing factors for the household decision structure, individual latent preferences, and influence of past viewing behavior. Since influence factors are demographic variables, managers can better predict future viewing behavior based on individual and household-level demographic information, and can have greater understanding of decision structures among different households.

Here we highlight our findings in terms of household decision structure, individual latent preferences, and influence of past viewing behavior.

Overall, there exists a dictator for television viewing decisions at weekday primetime in majority of families, though the propensity decreases for families with higher income levels, higher education levels, or more children. Among households with autocratic decision mode, father is the dictator in most cases. This indicates that adult males normally have dominant role in Hong Kong society, though this trend decreases as education level goes up and children grow up. Consistent with the resource theory (Blood and Wolf, 1960) or the social power theory (French and Raven, 1959), we found that working status of the mother has significant impact on mother's dictatorship; a working mom has higher propensity to be the dictator. The results reveal that Internet accessibility has different impacts on family members' dictatorship. Mothers have higher propensity to be the dictator in families with Internet access, while children have lower propensity to be dictators in families with Internet access. These results indicate that Internet has high propensity to be a substitute entertainment activity to television viewing for younger generation than for the older generation. The propensity for sons to be dictators is lower when there is Internet access in the family and when the family has more than one child.

We also found interesting patterns of interactions among family members. Overall, consistent with the gender schema theory (Bem, 1985) or gender theory (West and Zimmerman, 1987), dyads of the same gender have higher propensity to have coalition than dyads of different genders. Also interactions of mother-children dyads are stronger than those of father-children dyads, which is consistent with the traditional wisdom that mothers normally spend more time with children. One interesting finding of stepwise logistic regressions is that when children grow up, father-mother interaction has higher propensity to be coalition, while father-children and mother-children interactions have lower propensity to be coalition or higher propensity to be collision. This reflects one of the current social phenomena that parent-child relationships are less close than before after children grow up. In addition, we found that the popularity of Internet is accelerating this trend, with decreased propensity for parent-child relationship to be coalition in families with Internet access. Also, parents-children interactions vary along households with different income levels, with propensity for parents-children interactions to be collision being lower in families with medium income than low income. This is consistent with the traditional wisdom that middle-class families put more emphasis on children's education compared with high and lower-class families. Finally, consistent with the normal impression, working moms spend less time with children than housewives, leading to lower propensity for mother-child relationship to be coalition.

In terms of individual latent preferences, overall, dramas on TVB are much more popular than those on ATV. While "love" and "professional" are the most favorite drama types on TVB, "history" and "comedy" are the most favorite drama types on ATV. Stepwise logistic regressions further reveal that individual latent preferences across different drama types, family members and channels can be explained with demographic variables. For example, fathers in high income families have lower propensities to like "cops" most on TVB than those in low income families; working moms have higher propensities to like "professional" most on TVB than housewives; daughters have higher propensities to like "professional" and "action" most when they grow up, while sons have higher propensities to like "comedy" and "history" when they grow up.

Finally, we found different patterns for programme inheritance, state dependencies, and channel inheritance across different family members and families. Overall programme inheritance has lower propensity to be positive for family members in high income and high education families. Working moms have lower programme inheritance than housewives, and Internet accessibility leads to lower programme inheritance for fathers, while it leads to higher programme inheritance for children. Across the three types of state dependence, the second state dependence has the highest probability to be positive and the third state dependence the lowest.

Stepwise logistic regressions further reveal some interesting findings. For example, fathers in high income families have higher switching intentions, leading to lower propensity for the first and third state dependence to be positive. Working moms have higher switching intentions, leading to lower propensity for the second and third state dependence to be positive. And children in families with Internet access have higher switching propensity. Similarly, channel inheritance is higher for TVB than for ATV, with the highest probability to be positive for father and the lowest for mother. Stepwise logistic regressions reveal that the propensity for channel inheritance to be positive is higher for older fathers and mothers.

The above results make theoretical and managerial contributions in many different aspects:

First, the results can help managers understand the household decision structure and television viewing behaviors. For example, whether there exists a dictator indicates whether the household decision structure is democratic or autocratic, and who would be the dictator if the household decision structure is autocratic. This can help a company better understand potential target consumers. Interactions among household members can also provide insights into the household decision structure. By separating the latent preference from the final response, managers can have better understanding of target consumers. The influence of past viewing behaviors can provide insights into repeat viewing patterns among audiences and help managers evaluate advertising effectiveness. Secondly, the current research also illustrates theories proposed in previous research with real data. For example, the current research found significant gender effect along household members' interactions and latent preferences towards different programme types. To the best of our knowledge, the current research is the first to use real data to demonstrate the gender effect along different dimensions. Finally, the results also tap several hot topics in the society. For example, how mother's working status influences family members' viewing behavior, how the Internet influences our daily entertainment activities, and how family members' relationships with each other vary with different income and education levels.

CHAPTER 7 GENERAL CONCLUSIONS

In this section, we discuss how our proposed model and empirical findings are relevant to marketing academicians and practitioners. Firstly, we propose an integrated television viewing choice model which can achieve high prediction accuracy and provide behavioral explanations for the household decision process. We also contribute to the literature of group decision making by proposing a three-stage group decision making framework which is applicable to other marketing situations (e.g., group purchase, group decision). We highlight these contributions by comparing with Yang et al. (2006, 2010). Lastly, limitations and future research directions are discussed.

7.1 Summary

As stated in Chapter 1, the main objectives of the current research are 1) building an integrated television viewing choice model to achieve high prediction accuracy by incorporating four important factors (programme type, channel effect, family influence, and effect of past viewing behaviors) together; 2) explaining the decision making process for household television viewing.

According to our results described in Chapter 5 and 6, the dynamic model outperforms four sets of benchmarks including current industry practices and the traditional individual-level model. Hence practitioners can use the proposed model for more accurate television rating predictions, which are very important for advertising planning, programme scheduling, etc. In addition, comparison of the proposed model with the traditional individual-level model suggests that models that do not consider family influence lead to biased parameter estimation and lower prediction accuracy.

Beyond the high prediction power, the proposed model also achieves high explanatory power towards the household decision making process. The model's estimates provide indications about the household decision structure, individual latent preferences, and the effect of past viewing behavior. For the household decision structure, model estimates can help understand the household decision mode, the dictator (if any) in the family, and interactions among family members. For example, we found that though the decision structure has substantial heterogeneity across families, and most family decision modes are democratic, among autocratic families, the father normally is the dictator. For individual latent preferences, model estimates provide information on individuals' intrinsic utilities, and how they vary across different programme types and channels. For instance, we found that preferences for TVB dramas are normally higher than for ATV dramas. In respect of past viewing behavior, we can answer questions such as how does it impact later viewing choices when the viewer watches previous timeslots. The empirical results show that the effect of past viewing behavior varies across different family members, and normally the effect on females is higher than that on males. Figure 7.1 illustrates the factors incorporated in the current research.

---Insert Figure 7.1 about here---

7.2 Theoretical and Managerial Contributions

Our research mainly contributes to two streams of research: literature on television viewing choice modeling, and that on group decision making.

7.2.1 *Contributions to Television Viewing Choice Modeling Literature*

This research adds to the growing body of knowledge on television viewing choice. First, using the group decision making approach, we fill the gap in prior research by incorporating the family influence. Secondly, we separate individual latent preferences from the final behavior responses. Last, we integrate the three components of past viewing behavior, which is a first in this area. Next, we discuss each of the three contributions in greater detail.

Incorporating Family Influence via Group Decision Making Approach

Though television viewing is a family activity in most situations, prior literature has normally examined television viewing choice without considering the family influence except for the recent research by Yang and her colleagues (2006, 2010). Yang et al. (2006, 2010) examined household television viewing choice with approaches of either preference or behavioral interdependence. The current research is different as it uses a group decision making approach to model family influence. We show that this difference provides higher explanatory power about the decision process among family members. That is, the current research indicates not only the final solution of a conflict, but also the process of solving the conflict.

Actually, many researchers (Qualls, 1988, Arora and Allenby, 1999, etc.) have suggested the importance of process orientation in examining family decision making. Measures of the decision process, which tap a very different aspect of decision making than measures of the decision outcome, can provide many marketing implications. For example, the marketing communication plan would be more effective when it is delivered to decision makers rather than to others in the group. Hence knowledge of influence patterns among household members and the decision process are very important for design of marketing communication plans.

Separating Individual Latent Preference from Final Behavior Response

Another important feature of our model is that it allows separation of a family member's initial preference from the final response during television viewing. Since the latent preference is unobserved in secondary data of people meter, it is difficult to separate true product-related preferences from those relating to family maintenance needs (Davis, 1976). May be this is the reason why a viewer's final response is regarded as individual preference in most television viewing literature. In the current research, the proposed model allows inference of a viewers' latent preference from the observed final response, and the results show that the latent preference and the final response are two distinct decisions made in different decision stages. Thus, this approach provides a new angle to analyze people meter data for future research.

Understanding latent preferences has important marketing implications which can help television channels design targeting strategies and identify target consumers. In addition, separation of individual initial preference and the final response is also consistent with the established marketing theory that preferences or intentions don't definitely result in behaviors (Hoch and Loewenstein, 1991; Rook and Fisher, 1995).

Integrating Three Components of the Effect of Past Viewing Behavior

Lastly, we integrate three components of the effect of past viewing history. The three components are programme inheritance, state dependence and channel inheritance. To the best of our knowledge, the integrated approach has never been proposed in previous literature. Our findings suggest that the three components of past viewing behavior can provide many indications of family members' viewing choices along the temporal dimension. In addition, the three components vary across different demographic groups. For example, the current research finds that members in high-income families have higher state dependence than those in medium-income and low-income families.

A very important marketing implication of understanding the effect of past viewing behavior is designing effective marketing communication plans. To judge whether the advertising message has been effectively delivered to target consumers, we need to examine not only the ratings of the message (i.e. the number of times the message has been delivered to consumers), but also the reach rate (i.e. the number of consumers who have received this message). For example, an advertisement in a high rating programme may be watched by a limited number of consumers when there is high repeat viewing behavior among the consumers. While marketers of established brands normally want the advertising message to be watched by their target consumers with high frequency, marketers of new brands probability expect the message to be delivered to more consumers. Hence advertisers need to smartly define their communication strategy according to the past viewing behavior of potential viewers.

7.2.2 Contributions to Group Decision Making Literature

Three-stage Group Decision Making Framework

In addition to the above, another important contribution is that this work proposes and validates a three-stage group decision making framework using television viewing data. In prior research, the group decision making process normally ends up all group members going along with the group solution together. For example, in Su, Fern and Ye (2003), family decision making yields a final solution acceptable to all family members though some of them are not satisfied with it. However, it is not definitely the case in many situations. Using the current research context of television viewing as an example, some family members would choose to leave and not watch if their initial preferences are inconsistent with the household viewing choice.

Actually, there are many other situations in our daily lives and consumption processes. For instances, when a group of friends is deciding which restaurant to go for lunch, each of them may first vote for his/her favorite restaurant, and then the group picks one restaurant as the group decision. While some of them may go along with the group decision, some may drop out of the group and eat elsewhere when the group decision is not for their preferred restaurant. Another case is group purchasing, in which consumers make bulk purchases together in order to seek a good bargain from the company. Each member of the group may first vote for his/her favorite brand, then the group chooses one brand as the group decision to make purchase. As a consequence, some consumers may go along with the group decision to seek a good bargain, and some may drop out of the group and purchase individually when the group decision conflicts with their preferences. Nowadays, with development of the Internet, the group purchase trend is growing popular among consumers. There are even some websites on which consumers can post their purchase intentions and look for consumers with the same purchase intentions.

As discussed earlier, the group decision making process normally ends up with all group members going along with the group solution together (Su, Fern and Ye, 2003; Aribarg, Arora and Bodur 2002). In order to fill the gap in the literature, we propose a three stage decision making framework to depict the decision process in such situations comprising pre-decision stage, joint-decision stage and post-decision stage. In pre-decision stage, each group member makes the initial choice based on individual preference. Next, group members form a joint decision based on some decision rules in joint-decision stage. Finally, group members make their final responses in post-decision stage when they can choose either to follow the group decision or to drop out.

Marketing and Managerial Implications

The proposed framework implies several strategic recommendations for marketers where this kind of group decision process can be applied.

For example, understanding consumers is very important for companies to design marketing strategies. While most marketers define their consumers based on final consumption records, the current research suggests that it may not be definitely conclusive since consumers with high latent preference are actually the consumers attracted by the product itself.

Next, the proposed model can also facilitate allocation of marketing resources, and be used to effectively direct the content of marketing communication. For example, the additional knowledge that younger group members have more power to affect group purchase decision would suggest a reallocation of marketing resources such that younger group members are allocated a larger share of resources than what was being allocated to them based on consumption records alone.

Lastly, an important goal for most companies is to increase product off-take. In order to increase consumption of a particular type of product among groups, a viable strategy for a company is to target advertising to group members who have relatively low preference for the particular type of product but have high power for affecting group purchase decision. For example, we can plot each group member's power against his own preference for a given type of product. The lower right quadrant then associates with the case of high power and low preference. This offers a potential group of customers to target. First, this group has low preference, suggesting additional room for improvement. Second, they have high power for affecting others decisions.

7.3 Comparisons with Prior Research

As discussed before, though television viewing is a household activity under most circumstances, little research has been done to examine the household influence on individual television choice except for Yang and her colleagues (Yang, Narayan and Assael, 2006; Yang et al. 2010). Next, we highlight our contributions by comparing this work with Yang and her colleagues.

Summary of Yang et al. (2006, 2010)

Yang et al. (2006) estimated the interdependent of TV channel preference between husband and wife using a Bayesian estimation approach. They concluded that wives' viewing behavior depends more strongly on their husband's viewing behavior than husband's viewing behavior depends on their wives' viewing behavior. There also exist significant differences in parameters estimates of dependence across categories of television programmes. The differences in levels of spousal interdependence across households are partially explained by age and education levels of spouses.

Yang et al. (2010) have developed a model to capture multiple agents' simultaneous choice decisions over more than two alternatives. They apply the proposed model to a context of family member's television viewing, and simultaneously model whether TV is on, which type of programme is playing and which family members are watching. This proposed model allows us to estimate the individual's intrinsic and extrinsic preference from information of joint consumption with other members.

To conclude, we can see that Yang and her colleagues use either utility interdependence (Yang et al., 2006) or behavior interdependence (Yang et al., 2010) to study the family influence. Literature of interdependent consumer preferences differs from literature of group decision making. Specifically, models of interdependent consumer preferences do not focus on joint decision making; they rather focus on studying how one individual's behavior and his/her latent preferences (or behavioral intentions) are dependent on those of other individuals (Yang et al., 2006). On the contrary, literature of group decision making can illustrate the decision process more clearly than preference interdependence. We then make detailed comparisons between Yang et al. (2010) and the current research.

Detailed Comparisons with Yang et al. (2010)

Differences between Yang et al. (2010) and the current research are listed herein below.

Firstly, while Yang et al. (2010) is mainly a statistical model, the proposed model is mainly a behavioral model. Yang et al. (2010) derive the probability for each viewing choice by imposing statistical distribution assumptions based on the conditional approach of simultaneous-move game. However, the model cannot provide inferences on the detailed decision process among the family members. For example, how do family members solve the conflicts? And what is the decision role for each member of the family? As stated by their own, "we are not modeling a joint decision making per se in this study, ..." (Yang et al., 2010, page 26). On the contrary, the current models *are* modeling a joint decision making process by explicitly proposing a three-stage group decision framework to illustrate the whole decision process, and the probability for viewing choice is derived from the joint probability of the three stages. The three stages (individual viewing preference, household join decision, and final viewing response) provide clear explanations of behaviors towards how family members make decisions, and how they solve conflicts.

Secondly, while Yang et al. (2010) assume symmetric interactions among family members, this model allows both symmetric and asymmetric interactions. Prior research has indicated that personal interactions are directional, which is asymmetric in many situations (Schweinberger and Soukup, 1998). Indeed, Yang et al. (2006) found that the utility interdependence among husband and wife is asymmetric, not symmetric. However, Yang et al. (2010) impose symmetric behavior interactions on family members in statistical assumptions. On the contrary, the current model is able to relax the assumption of symmetric interactions, though interaction parameters along the two directions can not be separated.

Thirdly, while Yang et al. (2010) model only the relative preferences among different programme types, the current model incorporates competition among both programme types and channels by imposing different programme utilities across programme types and channels. As discussed in Chapter 2, programme type and channel have been defined as two major factors that determine television viewing choice (Darmon, 1976; Goettler and Shachar, 2001). In real life, competition among channels is routine since almost every viewer faces more than one channel choice. Hence we believe our approach is more realistic and aligns better with prior literature.

Fourthly, the current model provides more accurate television viewing choice prediction by incorporating three components of past viewing behavior simultaneously, i.e. programme inheritance, state dependence and channel inheritance. In Yang et al. (2010), only the dynamics of the state dependence is incorporated.

Fifthly, in the current research, we separately apply the model to each household's viewing records, leading to a one-on-one analysis of specific households. Yang et al. (2010) conduct estimation across all households in the sample and allow consumer heterogeneity at the same time. We conclude that the current model can provide more specific indications about household television viewing behaviors (e.g., family influence, latent preference and past viewing behaviors).

Table 7.1 summarises comparisons between Yang et al. (2010) and the current research. As illustrated, there are several other differences. For example, while Yang et al. (2010) have some difficulties in extending the family to more than three members, the current model is applicable to four or even five member families with controllable complications. While Yang et al. (2010) do not model the resistance utility, the current model incorporates the resistance utility. At last, Yang et al. (2010) use the MCMC estimation, while the current model uses mass level MLE estimation.

---Insert Table 7.1 about here---

7.4 Potential Limitations and Future Directions

Our empirical application is subject to several limitations, which also suggest opportunities for future research.

Firstly, because we only have one-year viewing records data, we are not able to examine the dynamic aspects over a longer period of time. For example, it would be interesting to explore whether dynamic change of demographics would lead to changed group decision modes.

Secondly, our analyses are limited to families with only one television set, which may lead to a non representative sample. While our approach is an important first step toward modeling complicated group decision making situations in households with more than one TV set, it is useful to extend the current work for future application.

Thirdly, though most of the important factors have been incorporated in the current model, more factors can be included to increase its prediction power. For example, individuals not watching television are engaged in activities such as reading, meeting friends, working, and so forth. Prior research finds that the utility of non-viewing activities differs among individuals according to their previous choice, time of the day, day of the week, and their idiosyncratic taste for the outside alternative (Goettler and Shachar, 2001). We can further build these factors to achieve a truly sophisticated television rating prediction model.

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FIGURES

Figure 1.1 Television Rating Business Model

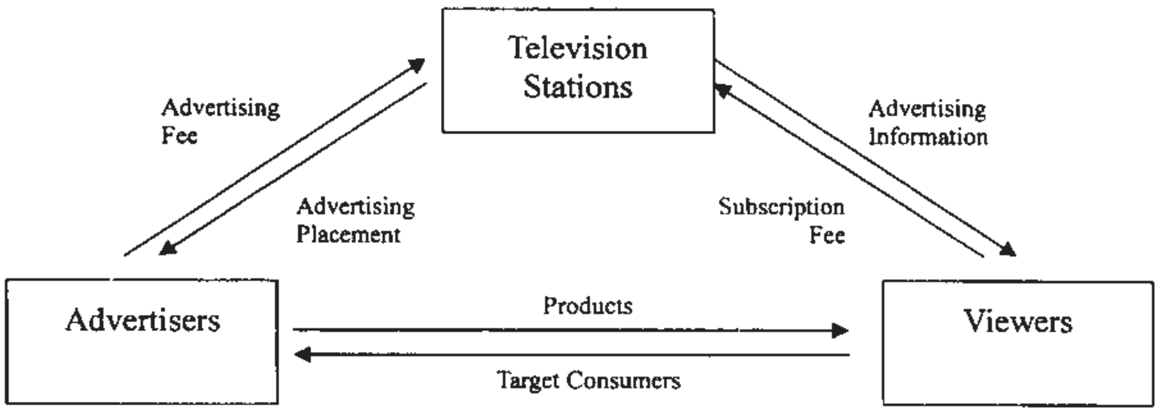


Figure 3.1 General Framework for Group Decision Making (Aribarg, Arora, and Bodur 2002)

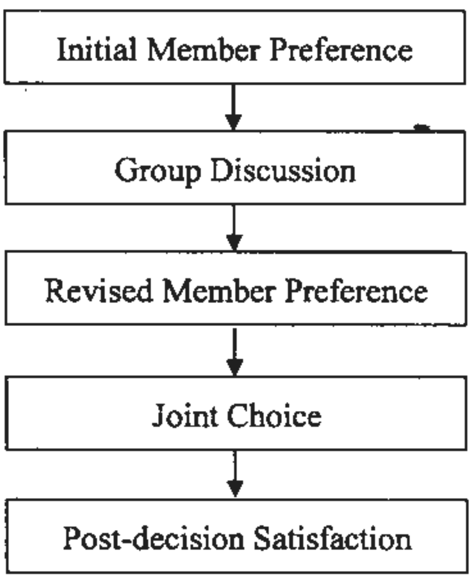


Figure 3.2 Framework for Household Television Viewing Choice Decision Process

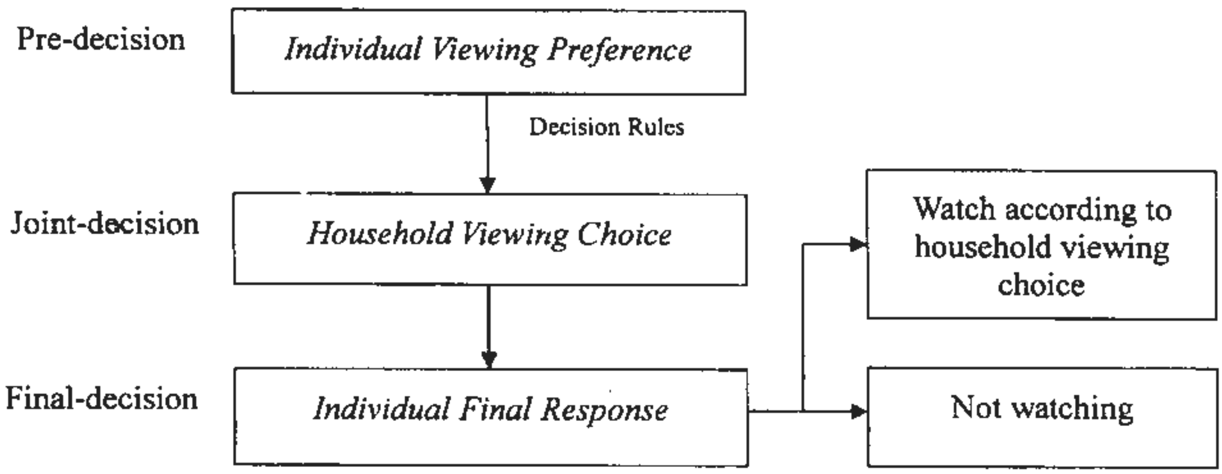


Figure 3.3 Pre-decision Stage: Individual Viewing Preference

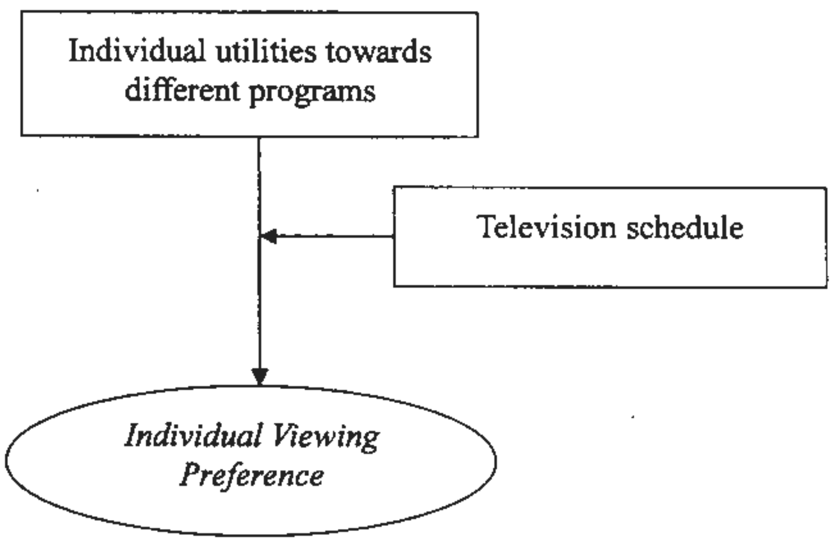


Figure 3.4 Joint-decision Stage: Household Viewing Choice

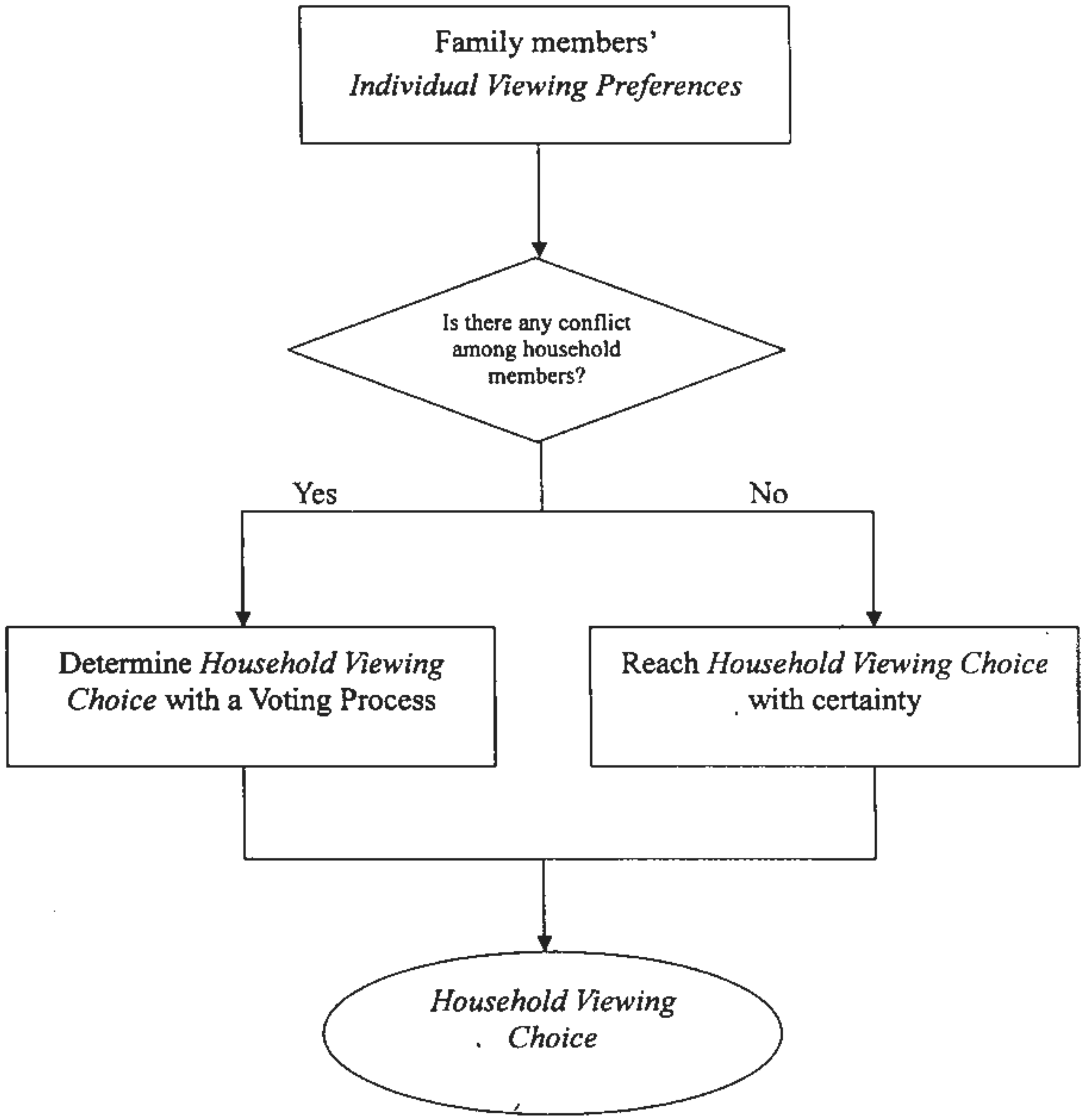


Figure 3.5 Post-decision Stage: Individual Final Response

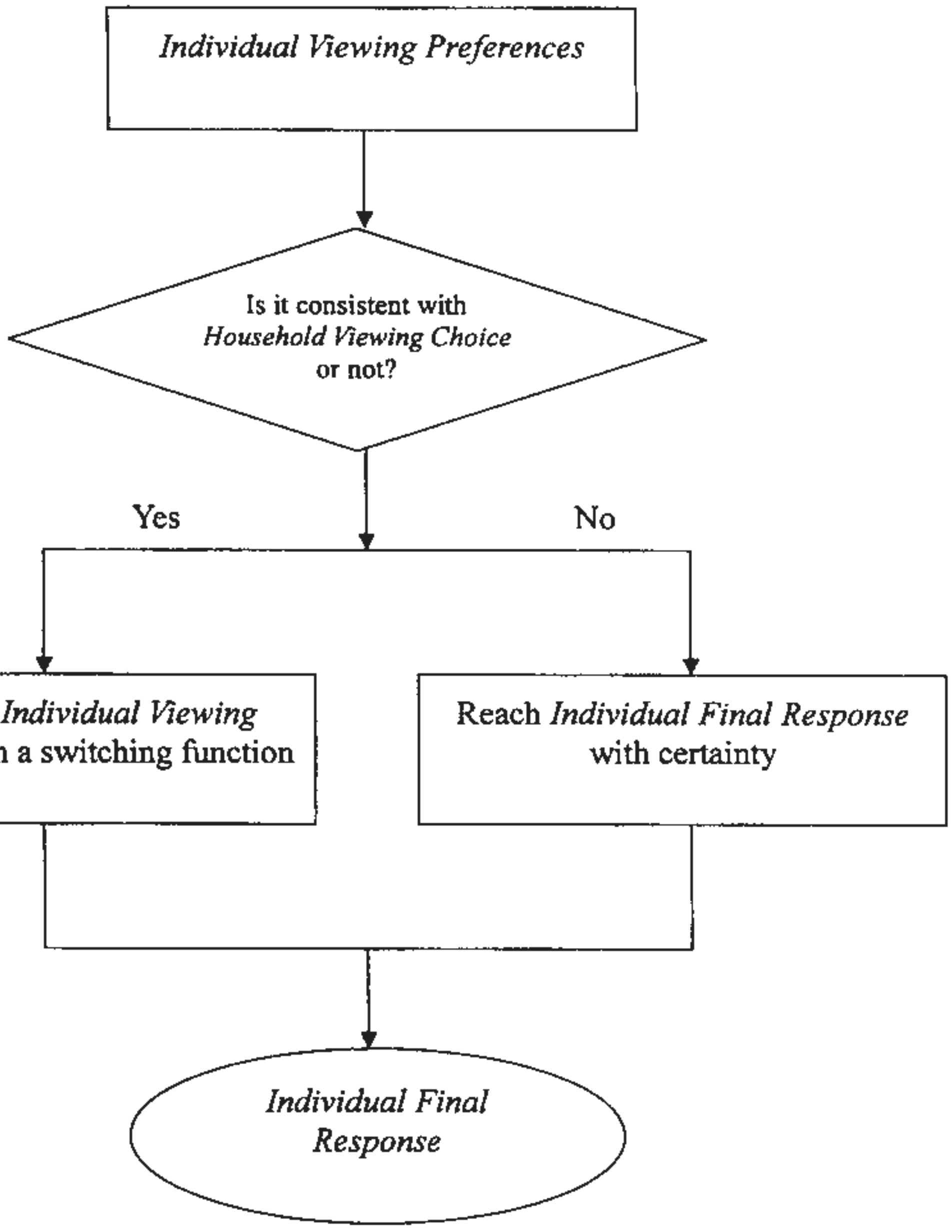


Figure 3.6 The Framework of Group Viewing Model (GVM)

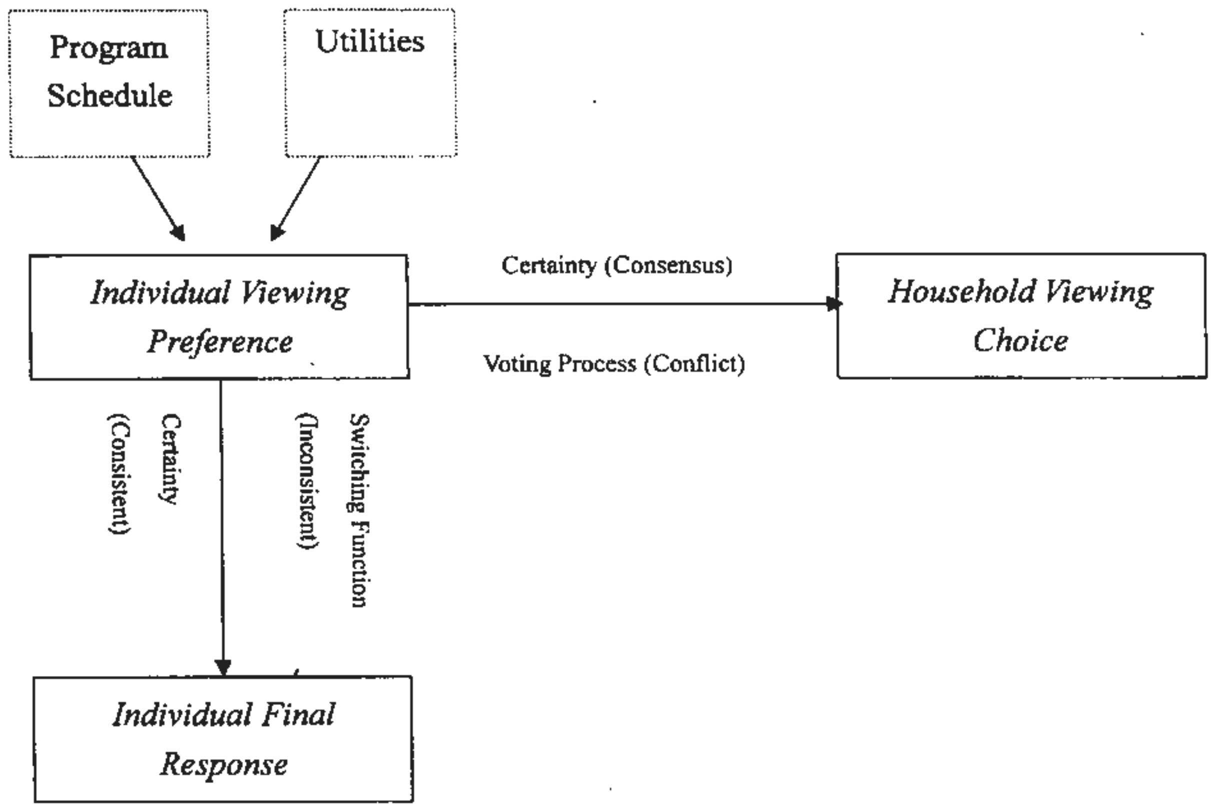


Figure 3.6 The Framework of Dynamic Group Viewing Model (DGVM)

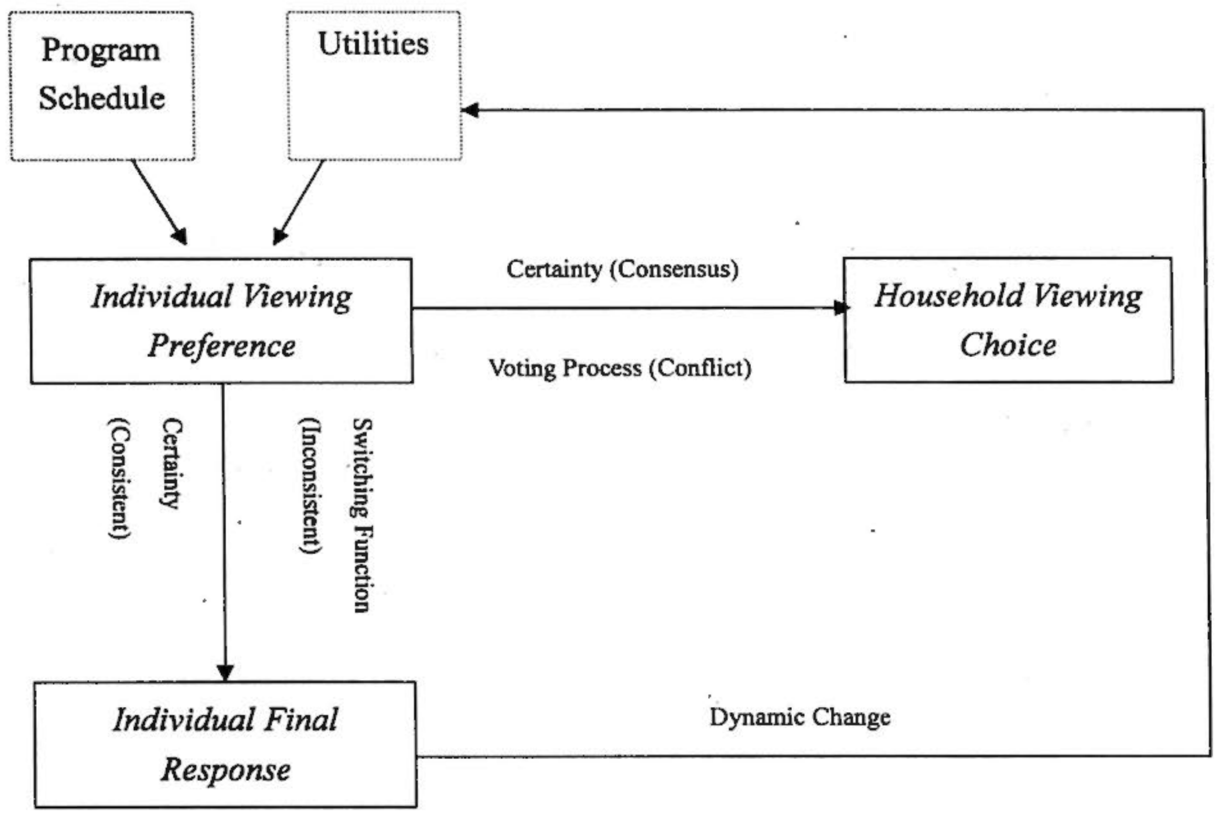


Figure 5.1a Shares of Three Viewing Options at Household-level and for Individual Family Members

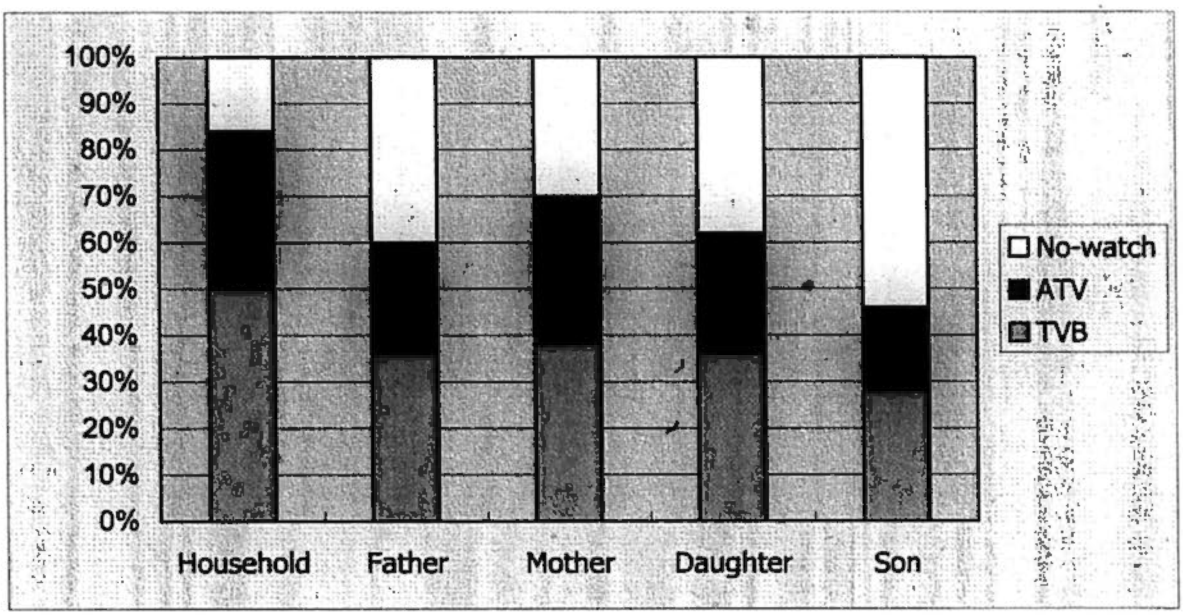


Figure 5.1b Shares of Six Types of Programs at Household-level and for Individual Family Members

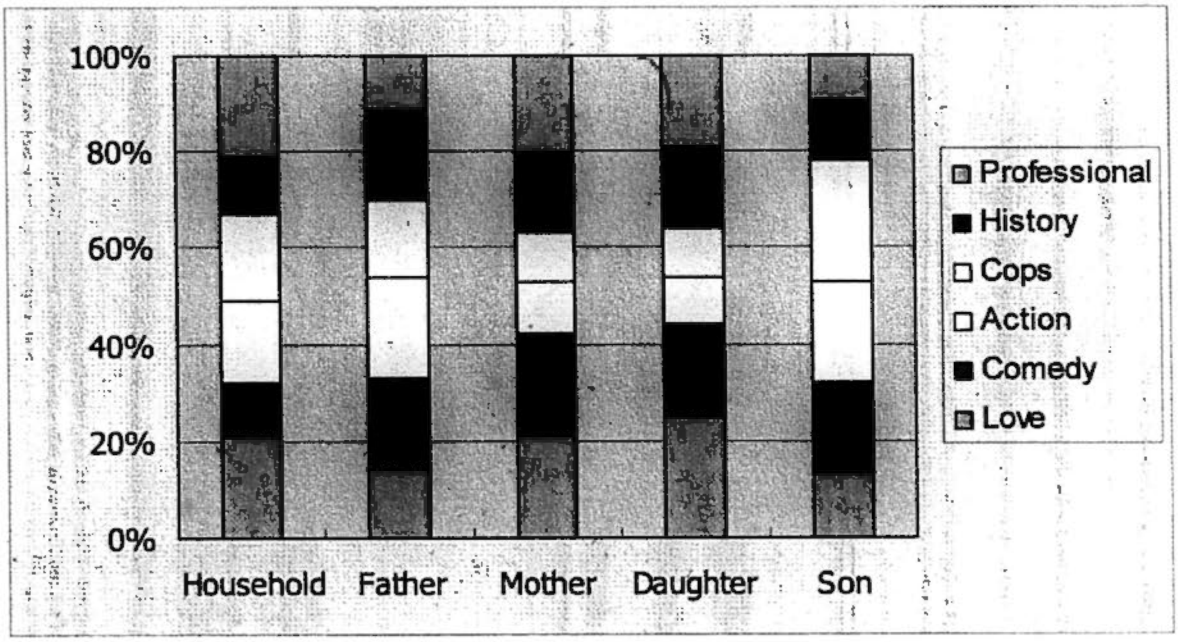
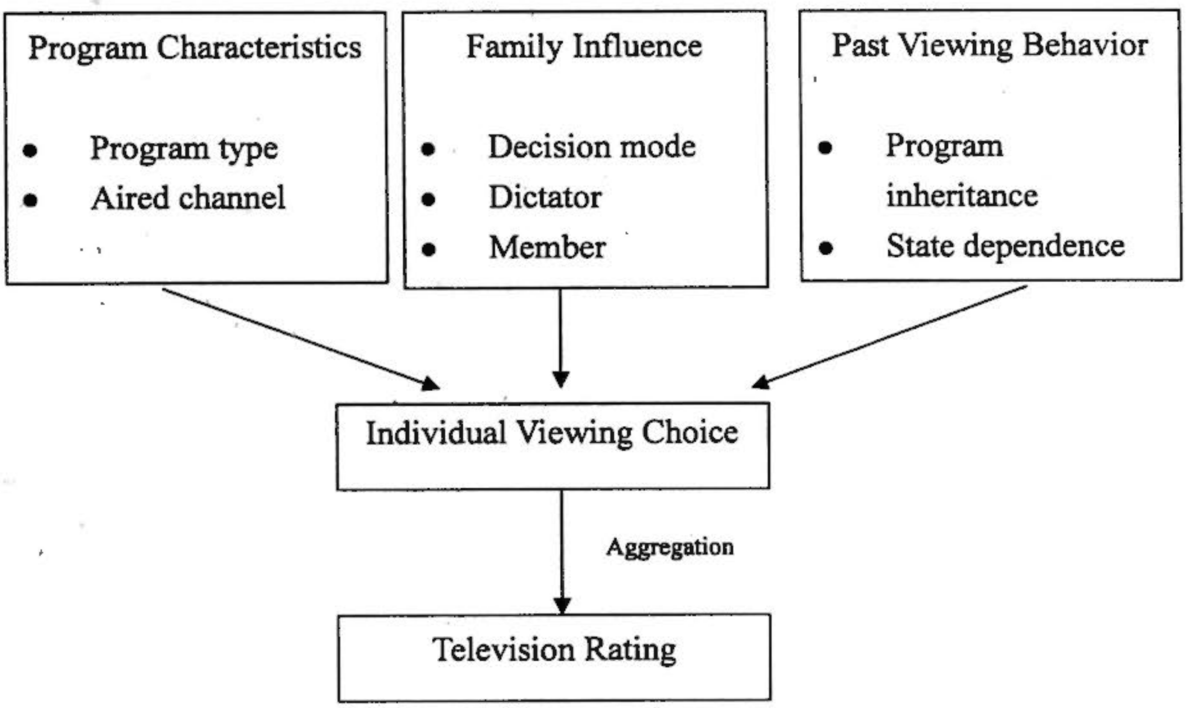


Figure 7.1 Factors Influence Television Rating Prediction



TABLES

Table 2.1 Effects of Past Viewing Behavior

Characteristics of Audience Flow	Effects of Past Viewing Behavior
Program loyalty	Program inheritance
Lead-in effect	State dependence
Channel loyalty	Channel inheritance

Table 3.1 Sample Viewing Records of a Three-member Family

Time	$R_{f(t)}$	$R_{m(t)}$	$R_{d(t)}$	$G_{(t)}$
1	1	1	0	1
2	2	2	2	2
3	3	3	3	3
......	......	......	......	......
N	$R_{f(t=n)}$	$R_{m(t=n)}$	$R_{d(t=n)}$	$G_{(t=n)}$

Table 3.2 All Possible Latent States Viewing Record of $(G=1, R_f=1, R_m=1, R_d=0)$

Latent states				Viewing records' probabilities conditional on each latent states			
No.	C_f	C_m	C_c	$P(G=1 \mid C_f, C_m, C_c)$	$P(R_f=1 \mid C_f, C_m, C_c)$	$P(R_m=1 \mid C_f, C_m, C_c)$	$P(R_c=0 \mid C_f, C_m, C_c)$
1	1	1	1	1	1	1	0***
2	1	1	0	1	1	1	1
3	1	0	1	1	1	0****	0***
4	0	1	1	1	0****	1	0***
5	1	0	0	1	1	0****	1
6	0	1	0	1	0****	1	1
7	0	0	1	1	0****	0****	0***
8	2	2	2	0*	${}_r\pi_{f\,k(t)}$	${}_r\pi_{m\,k(t)}$	${}_r\pi_{d\,k(t)}$
9	2	2	0	0*	${}_r\pi_{f\,k(t)}$	${}_r\pi_{m\,k(t)}$	1
10	2	0	2	0*	${}_r\pi_{f\,k(t)}$	0****	${}_r\pi_{d\,k(t)}$
11	0	2	2	0*	0****	${}_r\pi_{m\,k(t)}$	${}_r\pi_{d\,k(t)}$
12	2	0	0	0*	${}_r\pi_{f\,k(t)}$	0****	1
13	0	2	0	0*	0****	${}_r\pi_{m\,k(t)}$	1
14	0	0	2	0*	0****	0****	${}_r\pi_{d\,k(t)}$
15	0	0	0	0*	0****	0****	1
16	1	2	2	${}_g\pi_{k(t)}$	1	${}_r\pi_{m\,k(t)}$	${}_r\pi_{d\,k(t)}$
17	2	1	2	${}_g\pi_{k(t)}$	${}_r\pi_{f\,k(t)}$	1	${}_r\pi_{d\,k(t)}$
18	2	2	1	${}_g\pi_{k(t)}$	${}_r\pi_{f\,k(t)}$	${}_r\pi_{m\,k(t)}$	0***
19	1	1	2	${}_g\pi_{k(t)}$	1	1	${}_r\pi_{d\,k(t)}$
20	1	2	1	${}_g\pi_{k(t)}$	1	${}_r\pi_{m\,k(t)}$	0***
21	2	1	1	${}_g\pi_{k(t)}$	${}_r\pi_{f\,k(t)}$	1	0***
22	1	2	0	${}_g\pi_{k(t)}$	1	${}_r\pi_{m\,k(t)}$	1
23	2	1	0	${}_g\pi_{k(t)}$	${}_r\pi_{f\,k(t)}$	1	1
24	0	1	2	${}_g\pi_{k(t)}$	0****	1	${}_r\pi_{d\,k(t)}$
25	0	2	1	${}_g\pi_{k(t)}$	0****	${}_r\pi_{m\,k(t)}$	0***
26	1	0	2	${}_g\pi_{k(t)}$	1	0****	${}_r\pi_{d\,k(t)}$
27	2	0	1	${}_g\pi_{k(t)}$	${}_r\pi_{f\,k(t)}$	0****	0***

: Impose zero probability according to the first principle; **: Impose zero probability according to the second principle; ***: Impose zero probability according to the third principle; *: Impose zero probability according to the fourth principle.**

Table 3.3a Hit Rates under Different Conditions

	Small			Large		
	Democracy	Autocracy	Random	Democracy	Autocracy	Random
High Differentiation	100%	100%	100%	100%	100%	100%
Low Differentiation	91%	98%	92%	95%	99%	94%
No Differentiation	78%	81%	78%	88%	91%	90%

Table 3.3b Lifts under Different Conditions

	Small			Large		
	Democracy	Autocracy	Random	Democracy	Autocracy	Random
High Differentiation	1.00	1.00	1.00	1.00	1.00	1.00
Low Differentiation	0.90	0.90	0.91	0.97	0.96	0.96
No Differentiation	0.85	0.86	0.88	0.92	0.94	0.94

Table 4.1 Four Flow States

No.	Description	Model Specification	Coefficient
1	Family member *n* watches channel *k* at timeslot (*t*-1), and timeslot (*t*-1) is the beginning timeslot.	$Begin_{k(t-1)} * C_{nk(t-1)}$	${}_1\beta_{nk}$
2	Family member *n* watches channel *k* at timeslot (*t*-1), and timeslot *t* and (*t*-1) are the continuing timeslots.	–	–
3	Family member *n* watches channel *k* at timeslot (*t*-1), and timeslot *t* is the ending timeslot.	$End_{k(t)} * C_{nk(t-1)}$	${}_2\beta_{nk}$
4	Family member *n* watches channel *k* at timeslot (*t*-1), and timeslot (*t*-1) is the ending timeslot.	$End_{k(t-1)} * C_{nk(t-1)}$	${}_3\beta_{nk}$

Table 5.1 Percentage of Timeslots and Shows

Type	TVB				ATV			
	Dramas		Occasions		Dramas		Occasions	
	No.	%	No.	%	No.	%	No.	%
Love	7	18%	734	16%	8	21%	887	20%
Comedy	9	23%	907	20%	7	18%	704	16%
Action	7	18%	657	15%	8	21%	795	18%
Cops	6	15%	564	12%	6	15%	631	14%
History	5	13%	523	12%	6	15%	573	13%
Professional	6	15%	655	15%	4	10%	432	10%
Others	-	-	460	10%	-	-	478	10%

Table 5.2 Household Structure Composition

Household Structure	No. of Household
Father, Mother, Daughter	44
Father, Mother, Son	41
Father, Mother, two Daughters	14
Father, Mother, two Sons	17
Father, Mother, Daughter, and Son	24

Table 5.3 Variable Definitions and Summary Statistics

Variable	Description	Percentage
INCOME	0 < HK$20,000;	21.20%
(Household income)	1 = HK$20,000-$49,999;	56.50%
	2 =< HK$50,000	22.30%
EDU_P	0 < Secondary School/ Yijin;	54.60%
(Average education level)	1 => Secondary School/ Yijin	45.40%
N_C	0 = One;	41.88%
(Number of children)	1 = Two	58.12%
WORK_M	0 = Housewife;	34.52%
(Working status of mother)	1 = Working mom	65.48%
INTERNET	0 = No access;	47.73%
(Internet access)	1 = Available	52.27%
AGE_F	Age of father	43.73(12.14)*
AGE_M	Age of mother	36.19(10.32)*
AGE_D	Age of daughter	13.23(2.31)*
AGE_S	Age of son	11.76(4.61)*

* sample mean (sample standard deviation)

Table 5.4 Demographic Information for Household 10002016

Member ID	01	02	03	04
Role	Father	Mother	Daughter	Son
Age	50	48	15	12
Education	Associate Degree	Associate Degree	Secondary School	Secondary School
Monthly Income	$20,000 - $ 34,999	$7500 - $19,999	-	-

Table 5.5a First Order Weight Estimates (ω_n)

	Father	Mother	Daughter	Son
ω_n	5.80	3.27	0.21	-2.94

*Household ID: 10002016

Table 5.5b Second Order Weight Estimates (ω_{nm})

	Father-mother	Father-Daughter	Father-Son	Mother-Daughter	Mother-Son	Daughter-Son
ω_{nm}	54.56	-0.34	9.93	33.21	-11.09	-15.96

Table 5.6a Baseline Utility Estimates (δ_{njk})

	Father			Mother			Daughter			Son		
	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*
Love	8.06	(34.13)	(13.04)	46.45	(7.26)	19.60	44.23	32.11	38.17	6.19	(25.17)	(9.49)
Comedy	50.94	10.72	30.83	38.53	22.25	30.39	26.79	25.61	26.20	21.47	(12.43)	4.52
Action	38.83	27.21	33.02	(23.26)	(0.35)	(11.81)	16.48	(11.19)	2.65	21.52	38.96	30.24
Cops	28.11	(22.38)	2.87	8.16	(31.63)	(11.74)	11.53	22.19	16.86	46.64	23.33	34.99
History	(14.74)	35.82	10.54	2.42	23.82	13.12	(22.15)	4.19	(8.98)	14.31	(40.15)	(12.92)
Professional	(22.77)	14.39	(4.19)	39.46	(12.56)	13.45	34.02	(25.18)	4.42	(13.29)	(25.22)	(19.26)
Avg.	14.74	5.27	10.01	18.63	(0.96)	8.84	18.48	7.96	13.22	16.14	(6.78)	4.68

*Household ID: 10002016

Table 5.6b Initial Utility Estimates (η_{njk})

	Father			Mother			Daughter			Son		
	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*
Love	17.24	(44.40)	(13.58)	16.73	3.89	10.31	36.61	18.29	27.45	3.08	(11.91)	(4.42)
Comedy	43.67	1.51	22.59	17.16	16.18	16.67	18.58	38.73	28.66	18.58	(24.88)	(3.15)
Action	32.59	14.00	23.30	(18.10)	(7.61)	(12.86)	33.19	(13.86)	9.67	16.34	27.10	21.72
Cops	13.93	(14.17)	(0.12)	(0.20)	(37.25)	(18.73)	2.80	0.06	1.43	30.47	14.51	22.49
History	(21.53)	46.04	12.26	(12.26)	13.15	0.45	(34.98)	2.92	(16.03)	4.04	(41.41)	(18.69)
Professional	(36.04)	10.21	(12.92)	11.99	12.63	12.31	26.81	(25.62)	0.60	10.92	(25.45)	(7.27)
Avg.	8.31	2.20	5.25	2.55	0.17	(0.83)	13.84	3.42	8.63	13.91	(10.34)	1.78

*Household ID: 10002016

Table 5.6c Utility Difference (μ_{nyk})

	Father			Mother			Daughter			Son		
	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*
Love	(9.18)	10.27	0.55	29.72	(11.15)	9.29	7.62	13.82	10.72	3.11	(13.26)	(5.08)
Comedy	7.27	9.21	8.24	21.37	6.07	13.72	8.21	(13.12)	(2.46)	2.89	12.45	7.67
Action	6.24	13.21	9.73	(5.16)	7.26	1.05	(16.71)	2.67	(7.02)	5.18	11.86	8.52
Cops	14.18	(8.21)	2.99	8.36	5.62	6.99	8.73	22.13	15.43	16.17	8.82	12.50
History	6.79	(10.22)	(1.72)	14.68	10.67	12.68	12.83	1.27	7.05	10.27	1.26	5.77
Professional	13.27	4.18	8.73	27.47	(25.19)	1.14	7.21	0.44	3.83	(24.21)	0.23	(11.99)
Avg.	6.43	3.07	4.75	16.07	(1.12)	8.74	4.65	4.54	4.59	2.24	3.56	2.90

*Household ID: 10002016

Table 5.7a Program Inheritance Estimates (α_{njk})

	Father			Mother			Daughter			Son			Total		
	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*
Love	(1.82)	7.23	2.71	15.37	20.45	17.91	21.27	11.23	16.25	(0.89)	3.34	1.23	8.48	10.56	9.52
Comedy	13.38	13.28	13.33	15.38	(0.78)	7.30	3.29	4.28	3.79	7.77	12.35	10.06	9.96	7.28	8.62
Action	12.86	8.28	10.57	(0.22)	3.29	1.54	3.15	4.25	3.70	4.28	6.25	5.27	5.02	5.52	5.27
Cops	7.53	5.23	6.38	0.09	1.28	0.69	(1.37)	2.28	0.46	5.23	3.32	4.28	2.87	3.03	2.95
History	12.37	5.18	8.78	14.38	5.38	9.88	5.28	4.29	4.79	5.75	1.26	3.51	9.45	4.03	6.74
Professional	0.68	(1.28)	(0.30)	29.56	7.42	18.49	19.26	7.48	13.37	0.27	(0.18)	0.05	12.44	3.36	7.90
Avg.	7.50	6.32	6.91	12.43	6.17	9.30	8.48	5.64	7.06	3.74	4.39	4.06	8.04	5.63	6.83

*Household ID: 10002016

Table 5.7b State Dependence Estimates (${}_1\beta_{nk}$, ${}_2\beta_{nk}$, ${}_3\beta_{nk}$)

	Father			Mother			Daughter			Son			Total		
	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*
${}_1\beta_{nk}$	2.19	(8.37)	(3.09)	3.18	(2.26)	0.46	(5.21)	2.39	(1.41)	2.82	(4.29)	(0.74)	0.75	(3.13)	(1.19)
${}_2\beta_{nk}$	13.54	15.29	14.42	14.53	15.22	14.88	19.28	15.38	17.33	9.19	11.22	10.21	14.14	14.28	14.21
${}_3\beta_{nk}$	(0.29)	1.21	0.46	7.47	(1.83)	2.82	2.28	2.19	2.24	(0.49)	(3.38)	(1.93)	2.24	(0.45)	0.90
Average	5.15	2.71	3.93	8.39	3.71	6.05	5.45	6.65	6.05	3.84	1.18	2.51	5.71	3.56	4.64

*Household ID: 10002016

Table 5.7c Channel Inheritance Estimates (γ_{nk})

	Father			Mother			Daughter			Son			Total		
	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*	TVB	ATV	*Avg.*
Gamma	18.13	7.55	12.84	19.31	(1.29)	9.01	14.23	(4.28)	4.98	7.28	6.73	7.01	9.28	7.73	8.51

*Household ID: 10002016

Table 5.8a Training and Validation Results on Household 10002016

	Training				Validation			
	Household-level	Father	Mother	Daughter	Household-level	Father	Mother	Daughter
1	86%	80%	82%	77%	74%	68%	71%	65%
2	83%	77%	80%	76%	73%	68%	69%	68%
3	80%	73%	75%	73%	69%	65%	67%	64%
4	89%	81%	82%	80%	78%	77%	78%	74%
5	91%	86%	88%	77%	81%	78%	81%	77%
6	82%	78%	80%	73%	74%	69%	69%	69%
7	83%	78%	78%	81%	73%	68%	68%	66%
8	83%	73%	75%	71%	69%	67%	69%	65%
9	88%	80%	81%	79%	79%	72%	74%	75%
10	84%	79%	81%	79%	77%	69%	70%	70%
11	86%	82%	84%	82%	79%	71%	72%	72%
12	78%	72%	75%	70%	68%	64%	67%	70%
13	91%	85%	86%	83%	81%	77%	79%	80%
14	79%	73%	76%	71%	69%	62%	68%	69%
15	81%	76%	77%	75%	72%	64%	71%	64%
16	88%	77%	81%	76%	76%	66%	74%	64%
17	84%	77%	78%	75%	69%	61%	67%	59%
18	83%	73%	76%	72%	71%	62%	71%	61%
19	90%	81%	83%	78%	80%	72%	79%	72%
20	89%	86%	87%	86%	77%	72%	73%	72%
Average	85%	78%	80%	77%	74%	69%	72%	69%

*Household ID: 10002016

Table 5.8b Training and Validation Results Compared with Benchmarks

	Basic		Time-adjusted		Drama-adjusted		Individual-level	
	Individual-level	Household-level	Individual-level	Household-level	Individual-level	Household-level	Individual-level	Household-level
Training	2.06	2.13	1.78	1.93	1.84	1.87	1.35	1.76
Validation	2.18	2.28	1.83	1.88	1.76	1.66	1.39	1.71

Table 6.1 Demographic Variables

Variable	Description
INCOME[1]	0 = If household monthly income < $20,000;
(Household income)	1 = If household monthly income >= $20,000 and < $50,000
INCOME[2]	0 = If household monthly income < $20,000;
(Household income)	1 = If household monthly income >= $50,000
EDU_P	0 = If parents' average education level = < Secondary School/ Yijin;
(Education level)	1 = If parents' average education level = > Secondary School/ Yijin
N_C	0 = If there is only one child in the family;
(Number of children)	1 = If there are two children in the family
WORK_M	0 = If the mother is a housewife;
(mother's working status)	1 = If the mother is a working-mom
INTERNET	0 = No Access;
(Internet accessibility)	1 = Available
AGE_F	Age of father
AGE_M	Age of mother
AGE_C	Average age of the children
AGE_D	Age of daughter
AGE_S	Age of son

Table 6.2a Shares of Households with Different Decision Modes

Decision Mode	Democracy	Authority			
Decision Maker	-	Father	Mother	Daughter	Son
% among total households	44%	17%	15%	12%	12%

Table 6.2b Determinants of Household Decision Mode

	INTERCEPT	INCOME[1]	INCOME[2]	EDU_P	AGE_C	WORK_M	INTERNET	AGE_F	AGE_M	N_C	AGE_D	AGE_S
DM_H	0.53	0.67	-	0.19	-	-	-	-	-	0.26	-	-
D_f	0.33	-	-	-0.16	-0.78	-	-	-	-	-	-	-
D_m	0.26	-	-	-	-	0.69	0.06	-	-	-	-	-
D_d	0.17	-	-	-	-	-	-0.45	-	-	-0.23	0.67	-
D_s	0.29	-	-	-	-	-	-0.09	-	-	-0.14	-	-

Table 6.3a Shares of Three Types of Interactions across Different Dyads

Dyads	Coalition	Independence	Collision
Father-Mother	53%	18%	29%
Father-Daughter	30%	46%	24%
Father-Son	30%	38%	32%
Mother-Daughter	51%	15%	34%
Mother-Son	39%	18%	43%
Daughter-Daughter	49%	21%	30%
Son-Son	38%	34%	28%
Daughter-Son	30%	24%	46%

Table 6.3b Determinants of Interactions among Each Two Family Members

	INTERCEPT	INCOME[1]	INCOME[2]	EDU_P	AGE_C	WORK_M	INTERNET	AGE_F	AGE_M	N_C	AGE_D	AGE_S
$P(\omega_{fm}=1)$	0.44	0.53	-	-	0.36	-	-	-	-	-	-	-
$P(\omega_{fm}=2)$	0.25	-	-	-	-0.41	-	-	-	-	0.25	-	-
$P(\omega_{fd}=1)$	0.25	-	-	0.13	-	-	-	-	-	-0.22	-0.27	-
$P(\omega_{fd}=2)$	0.37	-	0.46	-	-	-	-	0.05	-	-	-	-
$P(\omega_{fs}=1)$	0.33	-	-	-	-	-	-0.20	-	-	-0.14	-	-
$P(\omega_{fs}=2)$	0.12	0.31	0.17	-0.23	-	-	-	-	-	-	-	-
$P(\omega_{md}=1)$	0.17	-	-	-	-	-0.11	-0.12	-	-	-	-	-
$P(\omega_{md}=2)$	0.66	0.25	-	-	-	-	-	-	-	-	-	-
$P(\omega_{ms}=1)$	0.39	-	-	-	-	-0.38	-	-	-	-0.26	-	-0.09
$P(\omega_{ms}=2)$	0.61	-	-	-0.22	-	-	-	-	0.29	-	-	0.16
$P(\omega_{cc}=1)$	0.48	-	-	-	-	-	-	-	-	0.35	-	-
$P(\omega_{cc}=2)$	0.29	-	-	-	-	-	-0.10	-	-	-	-	-

Table 6.4a **Shares of Top-2 drama types across Different Drama Types, Family Member, and Television Channels**

	Role	Love	Comedy	Action	Cops	History	Professional
TVB	Father	28%	42%	45%	39%	33%	30%
	Mother	48%	40%	23%	35%	37%	34%
	Daughter	39%	32%	35%	31%	36%	44%
	Son	21%	34%	56%	58%	28%	20%
	Total	42%	36%	37%	34%	29%	39%
ATV	Father	19%	39%	34%	52%	54%	19%
	Mother	50%	51%	31%	19%	31%	35%
	Daughter	49%	31%	42%	34%	28%	33%
	Son	28%	37%	51%	56%	23%	22%
	Total	27%	45%	31%	35%	50%	29%

Table 6.4b Determinants of Top-2 drama types across Different Drama Types, Family Members, and Television Channels

			INTERCEPT	INCOME[1]	INCOME[2]	EDU_P	N_C	WORK_M	INTERNET	AGE_F	AGE_M	AGE_C	AGE_D	AGE_S
TVB	Father	Love	0.70	-	-	-	-	-	-	-	-	-	-	-
		Comedy	0.46	-	-	-	0.37	-	-	-	-	0.16	-	-
		Action	0.02	-	-	-	-	-	-	-	-	-	-	-
		Cops	0.50	-0.83	-	-	-	-	-	-	-	-	-	-
		History	0.87	-	-	0.64	-	-	-	-	-	-	-	-
		Professional	0.25	-	-	-	-	-	-	-	-	-	-	-
	Mother	Love	0.44	-	-	-	-	-	-	-	-	0.54	-	-
		Comedy	0.34	0.32	-	-	0.77	-	-	-	-	-	-	-
		Action	0.18	-	-	-	-	-	-	-	-	0.26	-	-
		Cops	0.41	-	-	-	-	-	-	-	-	-	-	-
		History	0.23	-	-	-	-	-	-	-	0.47	-	-	-
		Professional	0.15	-	-	-	-	0.63	-	-	-	-	-	-
	Daughter	Love	0.58	-	-	-	-	-	-0.73	-	-	-	-	-
		Comedy	0.67	-	-	-	-	-	-	-	-	-	-	-
		Action	0.58	-	-	-	-	-	-	-	-	-	0.13	-
		Cops	0.14	-0.42	-0.16	-	-	-	-	-	-	-	-	-
		History	0.35	-	-	-	-	-	-	-	-	-	-	-
		Professional	0.24	-	-	-	-	-	-	-	-	-	0.34	-

	Son	Love	0.38	-	-	-	-	-	-	-	-	-	-	0.15
		Comedy	0.33	-	-	-	-	-	-0.11	-	-	-	-	0.37
		Action	0.06	-0.43	-	-0.52	-	-	-	-	-	-	-	-
		Cops	0.45	-0.08	-	-0.10	-	-	-	-	-	-	-	-
		History	0.57	-	-	-	-	-	-0.45	-	-	-	-	-
		Professional	0.66	-	-	-	-	-	-	-	-	-	-	-
ATV	Father	Love	0.37	-	-	-	-	-	-	-	-	-	-	-
		Comedy	0.62	-	-	-	0.20	-	-	-	-	-	-	-
		Action	0.53	-	-	-	-	-	-	-	-	-	-	-
		Cops	0.48	-	-	-	-	-	-	-	-	-	-	-
		History	0.47	-	-	0.13	-	-	-	-	-	-	-	-
		Professional	0.21	-	-	-	-	-	-	-	-	-	-	-
	Mother	Love	0.17	-	-	-	-	-	-	-	-	-	-	-
		Comedy	0.63	-	-	-	0.43	-	-	-	-	-	-	-
		Action	0.12	-	-	-	-	-	-	-	-	-	-	-
		Cops	0.22	-	-	-	-	-	-	-	-	-	-	-
		History	0.37	-	-	0.27	-	-	-	-	-	-	-	-
		Professional	0.55	-	-	-	-	-	-	-	-	-	-	-
	Daughter	Love	0.61	-	-	-	-	-	-0.44	-	-	-	-	-
		Comedy	0.29	-	-	-	0.24	-	-	-	-	-	-	-
		Action	0.51	-	-	-	-	-	-	-	-	-	-	-

	Cops	0.25	-0.23	-	-	-	-	-	-	-	-	-	-
	History	0.62	-	-	-	-	-	-0.14	-	-	-	-	-
	Professional	0.55	-	-	-	-	-	-	-	-	-	0.26	-
Son	Love	0.41	-	-	-	-	-	-	-	-0.33	-	-	-
	Comedy	0.78	-	-	-	-	-	-0.06	-	-	-	-	-
	Action	0.67	-0.14	-	-	-	-	-	-	-	-	-	-
	Cops	0.19	-	-	-0.37	-	-	-	-	-	-	-	-
	History	0.45	-	-	-	-	-	-0.91	-	-	-	-	-
	Professional	0.67	-	-	-	-	-	-	-	-	-	-	-

Table 6.5a Shares of Favorable Channel for Family Members

Role	TVB	ATV
Father	56%	44%
Mother	58%	42%
Daughter	73%	27%
Son	67%	33%
Total	68%	32%

Table 6.5b Determinants of Channel Favorability across Different Family Members

	INTERCEPT	INCOME[1]	INCOME[2]	EDU_P	AGE_C	WORK_M	INTERNET	AGE_F	AGE_M	N_C	AGE_D	AGE_S
Father	0.46	-	-	-	-	-	-	-	-	-	0.46	-
Mother	0.57	-	-	-	-	-0.40	-	-	0.51	0.37	-	-
Daughter	0.66	-0.18	-	-	-	-	-	-	-	-	-	-
Son	0.67	-	-	-	-	-	-0.32	-	-	-	-	-0.14

Table 6.6 Shares of Popularity Trends for family members, and for channels

			Increase	Flat	Decreasing
TVB	Father	Love	57%	11%	32%
		Comedy	48%	23%	29%
		Action	55%	21%	24%
		Cops	58%	19%	23%
		History	60%	13%	27%
		Professional	77%	9%	14%
	Mother	Love	51%	21%	28%
		Comedy	52%	13%	35%
		Action	69%	11%	20%
		Cops	50%	14%	36%
		History	50%	19%	31%
		Professional	69%	12%	19%
	Daughter	Love	58%	14%	28%
		Comedy	64%	15%	21%
		Action	53%	19%	28%
		Cops	58%	13%	29%
		History	57%	13%	30%
		Professional	49%	24%	27%

	Son	Love	51%	17%	32%
		Comedy	49%	14%	37%
		Action	46%	13%	41%
		Cops	57%	8%	35%
		History	56%	7%	37%
		Professional	54%	12%	34%
ATV	Father	Love	51%	10%	39%
		Comedy	49%	16%	35%
		Action	55%	21%	24%
		Cops	64%	18%	18%
		History	55%	24%	21%
		Professional	77%	9%	14%
	Mother	Love	51%	21%	28%
		Comedy	52%	13%	35%
		Action	47%	12%	41%
		Cops	48%	14%	38%
		History	51%	18%	31%
		Professional	71%	10%	19%
	Daughter	Love	58%	14%	28%
		Comedy	44%	15%	41%
		Action	55%	18%	27%

		Cops	57%	14%	29%
		History	54%	12%	34%
		Professional	48%	23%	29%
	Son	Love	61%	17%	22%
		Comedy	67%	11%	22%
		Action	46%	13%	41%
		Cops	67%	8%	25%
		History	63%	9%	28%
		Professional	64%	12%	24%

Table 6.7a **Shares of Positive Program Inheritance across Different Drama Types, Family Members, and Television Channels**

Channel	Role	Love	Comedy	Action	Cops	History	Professional	*Total*
TVB	Father	69%	68%	74%	76%	73%	64%	71%
	Mother	90%	84%	71%	73%	90%	82%	82%
	Daughter	91%	77%	86%	83%	82%	89%	85%
	Son	70%	75%	88%	83%	77%	81%	79%
	Total	80%	76%	80%	79%	80%	79%	79%
ATV	Father	60%	68%	69%	73%	61%	63%	66%
	Mother	79%	74%	78%	71%	65%	73%	73%
	Daughter	79%	71%	73%	82%	79%	79%	77%
	Son	65%	72%	80%	80%	74%	76%	75%
	Total	71%	71%	75%	76%	70%	73%	73%

Table 6.7b **Determinants of Program Inheritance across Different Family Members, Television Channels**

		INTERCEPT	INCOME[1]	INCOME[2]	EDU_P	AGE_C	WORK_M	INTERNET	AGE_F	AGE_M	N_C	AGE_D	AGE_S
TVB	Father	0.31	-0.51	-0.30	-	-	-	0.19	-	-	-	-	-
	Mother	0.70	-	-	-	-	-	-	-	-	-0.57	-	-
	Daughter	0.14	-	-	-0.47	-	-	-	-	-	-	-	-
	Son	0.23	-	-	-	-	-	-0.69	-	-	-	-	-
ATV	Father	0.18	-1.06	-0.10	-	-	0.41	-	-	-	-	0.24	-
	Mother	0.68	-	-	-	-0.43	-0.26	-	-	-	-0.42	-	-
	Daughter	0.22	-0.22	-0.20	-	-	-	-0.16	-	-	-	-	-
	Son	0.38	-0.32	-	-	-	-	-0.28	-	-	-	-	-0.67

Table 6.8a **Shares of Positive State Dependence across Different Family Members and Television Channels**

	Channel	Father	Mother	Daughter	Son	*Total*
$P({}_1\beta_{nt}=1)$	TVB	41%	42%	38%	34%	39%
	ATV	36%	31%	27%	29%	31%
$P({}_2\beta_{nt}=1)$	TVB	78%	85%	84%	81%	82%
	ATV	68%	75%	79%	68%	73%
$P({}_3\beta_{nt}=1)$	TVB	37%	65%	54%	39%	49%
	ATV	31%	53%	41%	32%	39%

Table 6.8b **Determinants of State Dependence across Different Family Members, Television Channels**

		INTERCEPT	INCOME[1]	INCOME[2]	EDU_P	AGE_C	WORK_M	INTERNET	AGE_F	AGE_M	N_C	AGE_D	AGE_S
$P(_1\beta_{nt}=1)$	Father	0.31	-0.62	-0.21	-	-	-	-	-	-	-	-	-
	Mother	0.70	-	-	-	-	-	-	-	-	-0.64	-	-
	Daughter	0.14	-	-	-	-	-	-	-	-	-	-	-
	Son	0.23	-	-	-	-	-	-0.17	-	-	-	-	-
$P(_2\beta_{nt}=1)$	Father	0.18	-	-	-	0.18	-	-	-	-	-	0.43	-
	Mother	0.68	-	-	-	-	-0.56	-	-	0.63	-	-	-
	Daughter	0.22	-	-	-	-	-	-	-	-	-	-	-
	Son	0.38	-	-0.49	-	-	-	-	-	-	-		-
$P(_3\beta_{nt}=1)$	Father	0.18	-0.38	-	-	-	-	-	0.50	-	-	-	-
	Mother	0.68	-	-	-0.52	-	-0.35	-	-	-	-	-	-
	Daughter	0.22	-	-	-0.15	-	-	-0.84	-	-	-	-	-
	Son	0.38	-	-	-	-	-	-	-	-	-	-	-

Table 6.9a **Shares of Positive Channel Inheritance across Different Family Members and Television Channels**

	Channel	Father	Mother	Daughter	Son	*Total*
$P(\gamma_{nt}=1)$	TVB	86%	81%	81%	77%	81%
	ATV	77%	69%	63%	61%	68%

Table 6.9b **Determinants of Channel Inheritance across Different Family Members, Television Channels**

	INTERCEPT	INCOME[1]	INCOME[2]	EDU_P	AGE_C	WORK_M	INTERNET	AGE_F	AGE_M	N_C	AGE_D	AGE_S
Father	0.18	-0.16	-	-	-	-	-	0.48	-	-	-	-
Mother	0.68	-	-	-	-	-0.42	-	0.22	-	-	-	-
Daughter	0.22	-	-	-	-	-	-	-	-	-	-	-
Son	0.38	-	-	-	-	-	-0.13	-	-	-	-	-

Table 7.1 Comparison between Current Research and Yang et al. (2010)

	Yang et al. (2010)	Current Research
1	Statistic model based on the conditional approach of simultaneous-move game.	Behavioral model based on a three-stage group decision making framework.
2	Assume symmetric behavioral interactions.	Allow asymmetric behavioral interactions.
3	Only model the relative preferences among different program types.	Explicit model the channel competitions.
4	Incorporate the dynamics of state dependence.	Incorporate there components of dynamics, including program inheritance, state dependence, and channel inheritance.
5	Conduct estimation across different households.	Conduct one on one analysis for specific household.
6	Do not model the utility for not watching.	Model the utility for not watching.
7	Use MCMC estimation.	Use mass-scale MLE estimation.
9	Difficult to extend on families with more than three members.	Applicable to families with four even five members.

APPENDIX 1 INTRODUCTION OF PEOPLE METER SYSTEM

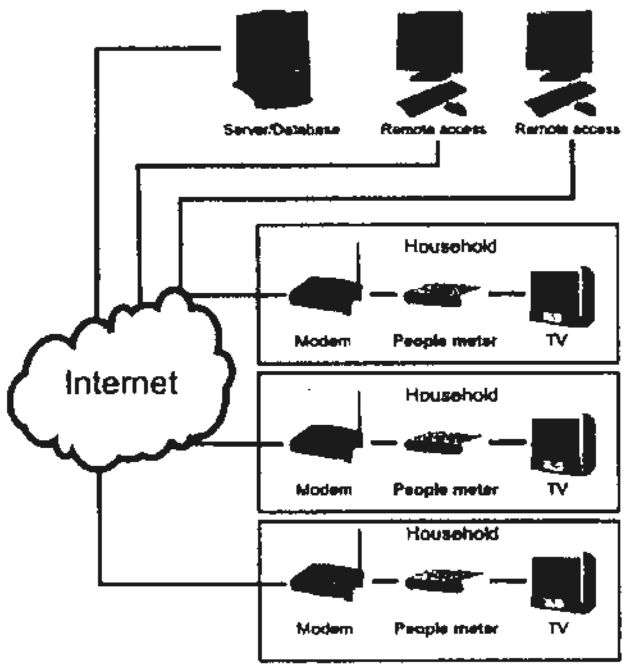
People meter system is consists of five small pieces of equipment: people-meter handset, people-meter display, collector box, TV detector and VCR smart probe.

To obtain the TV media Research, the media research company first selects a sample of households, or a "panel", which is made up of different types of households and individuals in the targeting area. Each panel household's viewing is then measured by the people-meter system. Figure 1 depicts the working process of people-meter system.

Families taking part in the TV Media Research are then request to install the "people-meter" equipment by trained engineers at home, and each individual family member makes a commitment to press their assigned number-button on the handset each time they start viewing, switching channels, and stop viewing. The display on the top of the TV set would show the number of household members who have pressed the button and the display screen flashes at intervals to remind family members to use the handset. The collector box and TV detector automatically record and store the time and the channel to which the TV is tuned, and viewers' information transmitted from the handset and the display. At 2:00am every night, the media research central computer makes a phone call to each household's collector box via the telephone line. The viewing information gathered during the day is transmitted back to the office within a short period of time.

The people-meter has been specially designed to be as unobtrusive as possible: no special in-home wiring is required, nor does the people-meter interfere in any way with the normal operation of the TV equipment. The silent phone call does not disturb the household, nor does it interfere with the telephone's normal operation. So the system provides an accurate minute-by-minute record of not only the set-tuning data but also the viewing data of individual household members.

Figure People Meter System



In Hong Kong, the service provider of television audience measurement is Nielsen Media Research which is part of the VNU Media Measurement & Information Group, a global leader in information services for the media and entertainment industries. It is a specialist in media research and has provided the television audience measurement service in Hong Kong since 2001.

APPENDIX 2 PROCESS TO FIND STARTING POINTS

We use SAS/IML to implement the proposed algorithm and find the likelihood estimates of (A_{njk} , ω_n , ω_{nm}) in equation (3.1)-(3.8). The large scale optimization does not guarantee convergence to global maximum likelihood estimate and the estimates are always biased by the initial values. Therefore, it is very important to select "good" starting points to avoid the parameter estimates being trapped in local optima (optional: with a poor initial value). Instead of using random starting points, we introduce a three-step process to find proper starting points in following context.

Step 1: Estimate utility parameters (A_{njk}) based on individual viewing preference sub-model in pre-decision stage

We first treat the individual viewing preference the same as the individual final response. That is, we assume the pre-decision stage is the whole decision process without considering the influence of household members, which is the similar as that in traditional television viewing choice model. By optimizing the individual channel choice records with the individual viewing preference sub-model in pre-decision stage, we estimate the utility parameters (A_{njk}).

Step 2: Estimate weighting parameters (ω_n ; ω_{nm}) based on the household viewing choice sub-model in joint-decision stage

Conditional on preference parameter estimates in step 1, we estimate the weighting parameters based on the household viewing choice sub-model in joint-decision stage.

Step 3: Estimate utility parameters (A_{njk}) and weighting parameters (ω_n ; ω_{nm}) based on the holistic decision process

Using the utility parameter estimates in step 1 and weighting parameter estimates in step 2 as the starting points, we estimate the two set of parameters again based on the holistic decision process. The results of parameter estimates in step 3 are hence the starting points for utility parameters and weighting parameters for later estimation.

APPENDIX 3 SAMPLE ESTIMATION PROGRAM

```
libname DS3m '/scratch/s061561/n3_2014';

proc sql;
    create table DS3m.DMtemp8 as
    select date, slot, tvbcode,allslot1,cntslot1,allday1,cntday1,

atvcode,allslot2,cntslot2,allday2,cntday2,tvbslot,atvslot,
          SB1, SB2, SE1, SE2, B1, B2, E1, E2,
          fptvb, fpatv, fnowatch,
          mptvb, mpatv, mnowatch,
          dptvb, dpatv, dnowatch,
          f1, f2, f3, m1, m2, m3, d1, d2, d3, g1, g2, g3
    from DS3m.DMtemp10;
quit;


proc sort data = DS3m.DMtemp8;
    by date slot;
run;

data DS3m.step1data1;
    set DS3m.DMtemp8;
    array Sftvb{3}(3*0);
    array Sfatv{3}(3*0);
    array Smtvb{3}(3*0);
    array Smatv{3}(3*0);
    array Sdtvb{3}(3*0);
    array Sdatv{3}(3*0);
    DTVB = 1;
    DATV = 1;
    format date date7.;
run;

proc iml;
    use DS3m.step1data1;
    read all into data;
    /*
        1-7:date, slot, tvbcode,allslot1,cntslot1,allday1,cntday1,
        8-12:atvcode,allslot2,cntslot2,allday2,cntday2,
        13-22:SB1, SB2, SE1, SE2, B1, B2, E1, E2,tvbslot,atvslot,
        23-25;fptvb, fpatv, fnowatch,
        26-28:mptvb, mpatv, mnowatch,
        29-31:dptvb, dpatv, dnowatch,
        32-43:f1, f2, f3, m1, m2, m3, d1, d2, d3, g1, g2, g3
        44-49:Sftvb1-3 Sfatv1-3
        50-55:Smtvb1-3 Smatv1-3
        56-61:Sdtvb1-3 Sdatv1-3
        62-63:DTVB DATV
    */

        NUM = nrow(data);
        tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
        atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
        Sf = J(1,3,0);
```

```
Sm = J(1,3,0);
Sd = J(1,3,0);
do i = 1 to NUM;
    if data[i,7] >= 4 then
    do;
        data[i,62] = 0;
        Sf[1:3] = 0;Sm[1:3] = 0;Sd[1:3] = 0;
        tvbcode = data[i,3];
        tvbtype = tvb_type[tvbcode];

        counter = 0;
        do j = 1 to 60;
            k  = i - j;
            if k < 1 then goto positionf1;
            if data[k,3] = tvbcode then
                do;
                    if data[i,7] - data[k,7] = 1 then
                    do;
                        Sf[1] = data[k,23];
                        Sm[1] = data[k,26];
                        Sd[1] = data[k,29];
                    end;
                    if data[i,7] - data[k,7] = 2 then
                    do;
                        Sf[2] = data[k,23];
                        Sm[2] = data[k,26];
                        Sd[2] = data[k,29];
                    end;
                    if data[i,7] - data[k,7] = 3 then
                    do;
                        Sf[3] = data[k,23];
                        Sm[3] = data[k,26];
                        Sd[3] = data[k,29];
                    end;
                    j = j + data[k,21];
                end;
            if data[k,7] - data[i,7] > 3 then goto positionf1;
        end;
        positionf1:
        data[i,44:46] = Sf[1,1:3];
        data[i,50:52] = Sm[1,1:3];
        data[i,56:58] = Sd[1,1:3];
    end;

    if data[i,12] >= 4 then
    do;
        data[i,63] = 0;
        Sf[1:3] = 0;Sm[1:3] = 0;Sd[1:3] = 0;
        atvcode = data[i,8];
        atvtype = atv_type[atvcode];

        counter = 0;
        do j = 1 to 60;
            k  = i - j;
            if k < 1 then goto positionf2;
            if data[k,8] = atvcode then
                if data[k,1] < data[i,1] then
                    do;
                        if data[i,12] - data[k,12] = 1 then
                        do;
                            Sf[1] = data[k,24];
```

```
                                        Sm[1] = data[k,27];
                                        Sd[1] = data[k,30];
                                    end;
                                    if data[i,12] - data[k,12] = 2 then
                                    do;
                                        Sf[2] = data[k,24];
                                        Sm[2] = data[k,27];
                                        Sd[2] = data[k,30];
                                    end;
                                    if data[i,12] - data[k,12] = 3 then
                                    do;
                                        Sf[3] = data[k,24];
                                        Sm[3] = data[k,27];
                                        Sd[3] = data[k,30];
                                    end;
                                    j = j + data[k,22];
                                end;
                        if data[k,12] - data[i,12] > 3 then goto positionf2;
                    end;
                    positionf2:
                    data[i,47:49] = Sf[1,1:3];
                    data[i,53:55] = Sm[1,1:3];
                    data[i,59:61] = Sd[1,1:3];
                end;
            end;
        create DS3m.step1data2 var{
            date slot tvbcode allslot1 cntslot1 allday1 cntday1
            atvcode allslot2 cntslot2 allday2 cntday2
            SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
            fptvb fpatv fnowatch
            mptvb mpatv mnowatch
            dptvb dpatv dnowatch
            f1 f2 f3 m1 m2 m3 d1 d2 d3 g1 g2 g3
            Sftvb1 Sftvb2 Sftvb3 Sfatv1 Sfatv2 Sfatv3
            Smtvb1 Smtvb2 Smtvb3 Smatv1 Smatv2 Smatv3
            Sdtvb1 Sdtvb2 Sdtvb3 Sdatv1 Sdatv2 Sdatv3
            DTVB DATV
        };
        append from data;
    quit;

    proc iml;
        use DS3m.step1data2;
        read all into data;
        /*
            1-7:date, slot, tvbcode,allslot1,cntslot1,allday1,cntday1,
            8-12:atvcode,allslot2,cntslot2,allday2,cntday2,
            13-22:SB1, SB2, SE1, SE2, B1, B2, E1, E2,tvbslot,atvslot,
            23-25;fptvb, fpatv, fnowatch,
            26-28:mptvb, mpatv, mnowatch,
            29-31:dptvb, dpatv, dnowatch,
            32-43:f1, f2, f3, m1, m2, m3, d1, d2, d3, g1, g2, g3
            44-49:Sftvb1-3 Sfatv1-3
            50-55:Smtvb1-3 Smatv1-3
            56-61:Sdtvb1-3 Sdatv1-3
            62-63:DTVB DATV
        */
        /*
            u:1-7:tvb, 8-14:atv
            duta:15-21, 22-28
            alpha:29-49:tvb, 50-70:atv
```

```
        beta:71-74
        gamma:75-76
        k1:77
    */

    /* F Part */
    start Funcf(F) global(data);
        *NUM = 100;
        NUM = nrow(data);
        tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
        atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
        sum = 0;
        do i = 1 to NUM;
            tvbcode = data[i,3];
            tvbtype = tvb_type[tvbcode];
            atvcode = data[i,8];
            atvtype = atv_type[atvcode];

            Uf1 = data[i,62]*F[tvbtype] + (1-data[i,62])*(F[14+tvbtype]
+ F[28+(tvbtype-1)*3+1]*data[i,44] + F[28+(tvbtype-1)*3+2]*data[i,45] +
F[28+(tvbtype-1)*3+3]*data[i,46])
                +
F[71]*data[i,17]+F[72]*data[i,18]+F[73]*data[i,19]+F[74]*data[i,20]+F
[75]*data[i,13]+F[76]*data[i,15];
            Uf2 = data[i,63]*F[7+atvtype] +
(1-data[i,63])*(F[21+atvtype] + F[49+(atvtype-1)*3+1]*data[i,47] +
F[49+(atvtype-1)*3+2]*data[i,48] + F[49+(atvtype-1)*3+3]*data[i,49])
                +
F[71]*data[i,63]+F[72]*data[i,18]+F[73]*data[i,19]+F[74]*data[i,20]+F
[75]*data[i,14]+F[76]*data[i,16];
            Cf = Uf1*data[i,32] + Uf2*data[i,33] + F[77]*data[i,34];
            sum = sum - log(exp(Uf1-Cf)+exp(Uf2-Cf)+exp(F[77]-Cf));
        end;
    return (sum);
    finish Funcf;

    /* M Part */
    start Funcm(M) global(data);
        *NUM = 100;
        NUM = nrow(data);
        tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
        atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
        sum = 0;
        do i = 1 to NUM;
            tvbcode = data[i,3];
            tvbtype = tvb_type[tvbcode];
            atvcode = data[i,8];
            atvtype = atv_type[atvcode];

            Um1 = data[i,62]*M[tvbtype] + (1-data[i,62])*(M[14+tvbtype]
+ M[28+(tvbtype-1)*3+1]*data[i,50] + M[28+(tvbtype-1)*3+2]*data[i,52] +
M[28+(tvbtype-1)*3+3]*data[i,53])
                +
M[71]*data[i,17]+M[72]*data[i,18]+M[73]*data[i,19]+M[74]*data[i,20]+M
[75]*data[i,13]+M[76]*data[i,15];
            Um2 = data[i,63]*M[7+atvtype] +
(1-data[i,63])*(M[21+atvtype] + M[49+(atvtype-1)*3+1]*data[i,54] +
M[49+(atvtype-1)*3+2]*data[i,55] + M[49+(atvtype-1)*3+3]*data[i,56])
                +
M[71]*data[i,17]+M[72]*data[i,18]+M[73]*data[i,19]+M[74]*data[i,20]+M
[75]*data[i,14]+M[76]*data[i,16];
```

```
            Cm = Um1*data[i,35] + Um2*data[i,36] + M[77]*data[i,37];
            sum = sum - log(exp(Um1-Cm)+exp(Um2-Cm)+exp(M[77]-Cm));
        end;
    return (sum);
    finish Funcm;

    /* D Part */
    start Funcd(D) global(data);
        *NUM = 100;
        NUM = nrow(data);
        tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
        atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
        sum = 0;
        do i = 1 to NUM;
            tvbcode = data[i,3];
            tvbtype = tvb_type[tvbcode];
            atvcode = data[i,8];
            atvtype = atv_type[atvcode];

            Ud1 = data[i,62]*D[tvbtype] + (1-data[i,62])*(D[14+tvbtype]
+ D[28+(tvbtype-1)*3+1]*data[i,56] + D[28+(tvbtype-1)*3+2]*data[i,57] +
D[28+(tvbtype-1)*3+3]*data[i,58])
                +
D[71]*data[i,17]+D[72]*data[i,18]+D[73]*data[i,19]+D[74]*data[i,20]+D
[75]*data[i,13]+D[76]*data[i,15];
            Ud2 = data[i,63]*D[7+atvtype] +
(1-data[i,63])*(D[21+atvtype] + D[49+(atvtype-1)*3+1]*data[i,59] +
D[49+(atvtype-1)*3+2]*data[i,60] + D[49+(atvtype-1)*3+3]*data[i,61])
                +
D[71]*data[i,17]+D[72]*data[i,18]+D[73]*data[i,19]+D[74]*data[i,20]+D
[75]*data[i,14]+D[76]*data[i,16];
            Cd = Ud1*data[i,38] + Ud2*data[i,39] + D[77]*data[i,40];
            sum = sum - log(exp(Ud1-Cd)+exp(Ud2-Cd)+exp(D[77]-Cd));
        end;
    return (sum);
    finish Funcd;

optn={1 2};
X=J(1,77,0);
Y=J(1,77,0);
Z=J(1,77,0);
con=J(2,79,.);
con[1,1:14] = -5;
con[2,1:14] = +5;
con[1,15:77] = 0;
con[2,15:77] = 1;
tc = repeat(.,12);
tc[1] = 4;
tc[2] = 10;
call nlpcg(rc,xres,"Funcf",X,optn,con,tc);
Create DS3m.imlstep1 from xres ;
Append from xres ;
call nlpcg(rc,xres,"Funcm",Y,optn,con,tc);
Append from xres ;
call nlpcg(rc,xres,"Funcd",Z,optn,con,tc);
Append from xres ;
quit;


/*****************************************************************
```

```
************************/
/* Evaluation */
proc sql;
    create table DS3m.stepleva0 as
    select date,slot,
        tvbcode,allslot1,cntslot1,allday1,cntday1,
        atvcode,allslot2,cntslot2,allday2,cntday2,
        SB1,SB2,SE1,SE2,B1,B2,E1,E2,tvbslot,atvslot,
        f1,f2,f3,m1,m2,m3,d1,d2,d3,g1,g2,g3
    from DS3m.stepldata1
    order by date, slot;
quit;

data DS3m.stepleva1;
    set DS3m.stepleva0;
    response1 = 3;
    response2 = 3;
    response3 = 3;
    group = 3;
    if f1 = 1 then response1 = 1;
    if f2 = 1 then response1 = 2;
    if m1 = 1 then response2 = 1;
    if m2 = 1 then response2 = 2;
    if d1 = 1 then response3 = 1;
    if d2 = 1 then response3 = 2;
    if g1 = 1 then group = 1;
    if g2 = 1 then group = 2;
    keep date slot
        tvbcode allslot1 cntslot1 allday1 cntday1
        atvcode allslot2 cntslot2 allday2 cntday2
        SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
        response1 response2 response3 group;
run;

data DS3m.stepleva2;
    set DS3m.stepleva1;
    eresponse1 = 0;
    eresponse2 = 0;
    eresponse3 = 0;
    egroup = 0;
    ep1tvbu = 0;
    ep1atvu = 0;
    k1 = 0;
    ep2tvbu = 0;
    ep2atvu = 0;
    k2 = 0;
    ep3tvbu = 0;
    ep3atvu = 0;
    k3 = 0;
    ef1 = 0;
    ef2 = 0;
    ef3 = 1;
    em1 = 0;
    em2 = 0;
    em3 = 1;
    ed1 = 0;
    ed2 = 0;
    ed3 = 1;
    eg1 = 0;
    eg2 = 0;
    eg3 = 1;
```

```
run;

proc iml;
    use DS3m.imlstep1;
    read all into par;

    use DS3m.stepleva2;
    read all into data;
    /*
        u:1-7:tvb, 8-14:atv
        duta:15-21, 22-28
        alpha:29-49:tvb, 50-70:atv
        beta:71-74
        gamma:75-76
        k1:77
    */
    tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
    atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};

 /*
         1-2:date slot
         3-7:tvbcode allslot1 cntslot1 allday1 cntday1
         8-12:atvcode allslot2 cntslot2 allday2 cntday2
         13-22:SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
         23-26:response1 response2 response3  group
         27-30:eresponse1 eresponse2 eresponse3 egroup
         31-39:ep1tvbu ep1atvu ek1 ep2tvbu ep2atvu ek2 ep3tvbu ep3atvu
 ek3
         40-51:ef1-3, em1-3, ed1-3,eg1-3,
 */

     do i = 1 to nrow(data);
         data[i,33] = par[1,77];
         data[i,36] = par[2,77];
         data[i,39] = par[3,77];
     end;
     do i = 1 to nrow(data);
         if data[i,7]  < 4 then
         do;
             tvbcode = data[i,3];
             tvbtype = tvb_type[tvbcode];
             data[i,31] = par[1,tvbtype] + par[1,71]*data[i,17] +
 par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
 par[1,75]*data[i,13] + par[1,76]*data[i,15];
             data[i,34] = par[2,tvbtype] + par[2,71]*data[i,17] +
 par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
 par[2,75]*data[i,13] + par[2,76]*data[i,15];
             data[i,37] = par[3,tvbtype] + par[3,71]*data[i,17] +
 par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
 par[3,75]*data[i,13] + par[3,76]*data[i,15];
         end;
         if data[i,12] < 4 then
         do;
             atvcode = data[i,8];
             atvtype = atv_type[atvcode];
             data[i,32] = par[1,7+atvtype] + par[1,71]*data[i,17] +
 par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
 par[1,75]*data[i,14] + par[1,76]*data[i,16];
             data[i,35] = par[2,7+atvtype] + par[2,71]*data[i,17] +
 par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
 par[2,75]*data[i,14] + par[2,76]*data[i,16];
```

```
            data[i,38] = par[3,7+atvtype] + par[3,71]*data[i,17] +
par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
par[3,75]*data[i,14] + par[3,76]*data[i,16];
        end;
    end;

    create DS3m.stepleva3 var{
         date slot
         tvbcode allslot1 cntslot1 allday1 cntday1
         atvcode allslot2 cntslot2 allday2 cntday2
         SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
         response1 response2 response3 group
         eresponse1 eresponse2 eresponse3 egroup
         ep1tvbu ep1atvu ek1 ep2tvbu ep2atvu ek2 ep3tvbu ep3atvu ek3
         ef1 ef2 ef3 em1 em2 em3 ed1 ed2 ed3 eg1 eg2 eg3
         };
    append from data;
quit;

data DS3m.stepleva4;
    set DS3m.stepleva3;
    if cntday1 < 4 & cntday2 < 4 then
    do;
         if ep1tvbu > ep1atvu & 2*ep1tvbu + ep1atvu > 1 then do;ef1 =
1;ef3=0;end;
         if ep1atvu > ep1tvbu & 2*ep1atvu + ep1tvbu > 1 then do;ef2 =
1;ef3=0;end;
         if ep2tvbu > ep2atvu & 2*ep2tvbu + ep2atvu > 1 then do;em1 =
1;em3=0;end;
         if ep2atvu > ep2tvbu & 2*ep2atvu + ep2tvbu > 1 then do;em2 =
1;em3=0;end;
         if ep3tvbu > ep3atvu & 2*ep3tvbu + ep3atvu > 1 then do;ed1 =
1;ed3=0;end;
         if ep3atvu > ep3tvbu & 2*ep3atvu + ep3tvbu > 1 then do;ed2 =
1;ed3=0;end;
    end;
run;

proc iml;
    use DS3m.stepleva4;
    read all into data;

    use DS3m.imlstep1;
    read all into par;
    Sf = J(1,3,0);
    Sm = J(1,3,0);
    Sd = J(1,3,0);
    tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
    atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
/*
          1-2:date slot
          3-7:tvbcode allslot1 cntslot1 allday1 cntday1
          8-12:atvcode allslot2 cntslot2 allday2 cntday2
          13-22:SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
          23-26:response1 response2 response3  group
          27-30:eresponse1 eresponse2 eresponse3 egroup
          31-39:ep1tvbu ep1atvu ek1 ep2tvbu ep2atvu ek2 ep3tvbu ep3atvu
ek3
          40-51:ef1-3, em1-3, ed1-3,eg1-3,
*/
    do i = 1 to nrow(data);
```

```
        if data[i,7] >= 4 then
        do;
            tvbcode = data[i,3];
            tvbtype = tvb_type[tvbcode];
            counter = 0;
            date = data[i,1];
            Sf[1:3] = 0;Sm[1:3] = 0;Sd[1:3] = 0;
                do j = 1 to 100;
                    k  = i - j;
                    if k < 1 then goto position1;
                    if data[k,3] = tvbcode then
                        if data[k,1] < data[i,1] then
                            do;
                                if data[k,1] < date then
                                    do;
                                        counter = counter + 1;
                                        date = data[k,1];
                                    end;
                                if counter = 4 then goto position1;
                                Sf[counter] =
Sf[counter]+data[i,40]/data[i,21];
                                Sm[counter] =
Sm[counter]+data[i,43]/data[i,21];
                                Sd[counter] =
Sd[counter]+data[i,46]/data[i,21];
                            end;
                end;
                position1:
                data[i,31] = par[1,14+tvbtype] + par[1,71]*data[i,17] +
par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
par[1,75]*data[i,13] + par[1,76]*data[i,15];
                data[i,34] = par[2,14+tvbtype] + par[2,71]*data[i,17] +
par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
par[2,75]*data[i,13] + par[2,76]*data[i,15];
                data[i,37] = par[3,14+tvbtype] + par[3,71]*data[i,17] +
par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
par[3,75]*data[i,13] + par[3,76]*data[i,15];
                data[i,31] = data[i,31] +
Sf[1]*par[1,28+(tvbtype-1)*3+1] + Sf[2]*par[1,28+(tvbtype-1)*3+2]  +
Sf[3]*par[1,28+(tvbtype-1)*3+3] ;
                data[i,34] = data[i,34] +
Sm[1]*par[2,28+(tvbtype-1)*3+1] + Sm[2]*par[2,28+(tvbtype-1)*3+2]  +
Sm[3]*par[2,28+(tvbtype-1)*3+3] ;
                data[i,37] = data[i,37] +
Sd[1]*par[3,28+(tvbtype-1)*3+1] + Sd[2]*par[3,28+(tvbtype-1)*3+2]  +
Sd[3]*par[3,28+(tvbtype-1)*3+3] ;
        end;
        if data[i,12] >= 4 then
        do;
            atvcode = data[i,8];
            atvtype = atv_type[atvcode];
            counter = 0;
            date = data[i,1];
            Sf[1:3] = 0;Sm[1:3] = 0;Sd[1:3] = 0;
                do j = 1 to 100;
                    k  = i - j;
                    if k < 1 then goto position2;
                    if data[k,8] = atvcode then
                        if data[k,1] < data[i,1] then
                            do;
                                if data[k,1] < date then
```

```
                                        do;
                                            counter = counter + 1;
                                            date = data[k,1];
                                        end;
                                    if counter = 4 then goto position2;
                                    Sf[counter] =
Sf[counter]+data[i,41]/data[i,22];
                                    Sm[counter] =
Sm[counter]+data[i,44]/data[i,22];
                                    Sd[counter] =
Sd[counter]+data[i,47]/data[i,22];
                                end;
                end;
                position2:
                atvcode = data[i,8];
                atvtype = atv_type[atvcode];
                data[i,32] = par[1,21+atvcode] + par[1,71]*data[i,17] -
par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
par[1,75]*data[i,14] + par[1,76]*data[i,16];
                data[i,35] = par[2,21+atvcode] + par[2,71]*data[i,17] -
par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
par[2,75]*data[i,14] + par[2,76]*data[i,16];
                data[i,38] = par[3,21+atvcode] + par[3,71]*data[i,17] -
par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
par[3,75]*data[i,14] + par[3,76]*data[i,16];
                data[i,32] = data[i,32] +
Sf[1]*par[1,49+(atvtype-1)*3+1] + Sf[2]*par[1,49+(atvtype-1)*3+2] +
Sf[3]*par[1,49+(atvtype-1)*3+3];
                data[i,35] = data[i,35] +
Sm[1]*par[2,49+(atvtype-1)*3+1] + Sm[2]*par[2,49+(atvtype-1)*3+2] +
Sm[3]*par[2,49+(atvtype-1)*3+3];
                data[i,38] = data[i,38] +
Sd[1]*par[3,49+(atvtype-1)*3+1] + Sd[2]*par[3,49+(atvtype-1)*3+2] +
Sd[3]*par[3,49+(atvtype-1)*3+3];
            end;

            if data[i,12] >= 4 | data[i,7] >= 4 then
            do;
                if data[i,31] > data[i,32] & 2*data[i,31] + data[i,32] > 1
then do;data[i,40] = 1; data[i,42]=0;end;
                if data[i,32] > data[i,31] & 2*data[i,32] + data[i,31] > 1
then do;data[i,41] = 1; data[i,42]=0;end;
                if data[i,34] > data[i,35] & 2*data[i,34] + data[i,35] > 1
then do;data[i,43] = 1; data[i,45]=0;end;
                if data[i,35] > data[i,34] & 2*data[i,35] + data[i,34] > 1
then do;data[i,44] = 1; data[i,45]=0;end;
                if data[i,37] > data[i,38] & 2*data[i,37] + data[i,38] > 1
then do;data[i,46] = 1; data[i,48]=0;end;
                if data[i,38] > data[i,37] & 2*data[i,38] + data[i,37] > 1
then do;data[i,47] = 1; data[i,48]=0;end;
            end;
        end;
        create DS3m.stepleva5 var{
            date slot
            tvbcode allslot1 cntslot1 allday1 cntday1
            atvcode allslot2 cntslot2 allday2 cntday2
            SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
            response1 response2 response3 group
            eresponse1 eresponse2 eresponse3 egroup
            ep1tvbu ep1atvu k1 ep2tvbu ep2atvu k2 ep3tvbu ep3atvu k3
            ef1 ef2 ef3 em1 em2 em3 ed1 ed2 ed3 eg1 eg2 eg3
```

```
        };
    append from data;
quit;


data DS3m.stepleva6;
    set DS3m.stepleva5;
    if ef1 = 1 then ef = 1;
    if ef2 = 1 then ef = 2;
    if ef3 = 1 then ef = 3;
    if em1 = 1 then em = 1;
    if em2 = 1 then em = 2;
    if em3 = 1 then em = 3;
    if ed1 = 1 then ed = 1;
    if ed2 = 1 then ed = 2;
    if ed3 = 1 then ed = 3;
run;

data DS3m.stepleva7;
    set DS3m.stepleva6;
    w1 = 0.333;
    w2 = 0.333;
    w3 = 0.333;

    p1v1 = 0;
    p1v2 = 0;
    if ef = 1 then p1v1 = 1;
    if ef = 2 then p1v2 = 1;
    p2v1 = 0;
    p2v2 = 0;
    if em = 1 then p2v1 = 1;
    if em = 2 then p2v2 = 1;
    p3v1 = 0;
    p3v2 = 0;
    if ed = 1 then p3v1 = 1;
    if ed = 2 then p3v2 = 1;

   vote1 = w1*p1v1 + w2*p2v1 + w3*p3v1;
   vote2 = w1*p1v2 + w2*p2v2 + w3*p3v2;

   if vote1 = 0 and vote2 = 0 then
   do;
         egroup = 3;
         eresponse1 = 3;
         eresponse2 = 3;
         eresponse3 = 3;
   end;
   if vote1 = 0 and vote2 ^= 0 then egroup = 2;
   if vote1 ^= 0 and vote2 = 0 then egroup = 1;
   if vote1 ^= 0 and vote2 ^= 0 then
   do;
         egroup1 = exp(vote1) / ( exp(vote1) + exp(vote2) );
         ran = ranuni(117);
         if ran < egroup1 then egroup = 1;
         else egroup = 2 ;
   end;

   if ( egroup = 1 ) and ( ef = 1) then eresponse1 = 1 ;
   if ( egroup = 1 ) and ( em = 1) then eresponse2 = 1 ;
   if ( egroup = 1 ) and ( ed = 1) then eresponse3 = 1 ;
```

```
if ( egroup = 1 ) and ( ef = 3) then eresponse1 = 3 ;
if ( egroup = 1 ) and ( em = 3) then eresponse2 = 3 ;
if ( egroup = 1 ) and ( ed = 3) then eresponse3 = 3 ;

if ( egroup = 2 ) and ( ef = 2) then eresponse1 = 2 ;
if ( egroup = 2 ) and ( em = 2) then eresponse2 = 2 ;
if ( egroup = 2 ) and ( ed = 2) then eresponse3 = 2 ;

if ( egroup = 2 ) and ( ef = 3) then eresponse1 = 3 ;
if ( egroup = 2 ) and ( em = 3) then eresponse2 = 3 ;
if ( egroup = 2 ) and ( ed = 3) then eresponse3 = 3 ;

  if (egroup = 1) and (ef = 2 ) then
   do ;
      switch = exp(ep1tvbu) / ( exp(ep1tvbu)  + exp(k1) );
      ran = ranuni(118) ;
     if ran < switch then eresponse1 = 1 ;
      else eresponse1 = 3 ;
   end ;

  if (egroup = 1) and (em = 2 ) then
   do ;
      switch = exp(ep2tvbu) / ( exp(ep2tvbu)  + exp(k2) );
      ran = ranuni(119) ;
     if ran < switch then eresponse2 = 1 ;
      else eresponse2 = 3 ;
   end ;

   if (egroup = 1) and (ed = 2 ) then
   do ;
      switch = exp(ep3tvbu) / ( exp(ep3tvbu)  + exp(k3) );
      ran = ranuni(120) ;
     if ran < switch then eresponse3 = 1 ;
      else eresponse3 = 3 ;
   end ;

  if (egroup = 2) and (ef = 1 ) then
   do ;
      switch = exp(ep1atvu) / ( exp(ep1atvu)  + exp(k1) );
      ran = ranuni(122) ;
     if ran < switch then eresponse1 = 2 ;
      else eresponse1 = 3 ;
   end ;

  if (egroup = 2) and (em = 1 ) then
   do ;
      switch = exp(ep2atvu) / ( exp(ep2atvu)  + exp(k2) );
      ran = ranuni(123) ;
     if ran < switch then eresponse2 = 2 ;
      else eresponse2 = 3 ;
   end ;

   if (egroup = 2 ) and (ed = 1 ) then
   do ;
      switch = exp(ep3atvu) / ( exp(ep3atvu)  + exp(k3) );
      ran = ranuni(124) ;
     if ran < switch then eresponse3 = 2 ;
      else eresponse3 = 3 ;
   end ;
run;
```

```
*****************************************************************;

data DS3m.h1(keep=date slot group egroup response1 response2 response3
eresponse1 eresponse2 eresponse3 );
    set DS3m.step1eva7;
run;
*****************************************************************;
proc freq data = DS3m.h1;
   tables group * egroup / chisq;

    tables response1 * eresponse1 / chisq;
    tables response2 * eresponse2 / chisq;
    tables response3 * eresponse3 / chisq;
run;


*****************************************************************;
*****************************************************************;


data DS3m.step2data1;
     set DS3m.step1data2;
     format date date7.;
run;

data DS3m.step2data2;
     set DS3m.step2data1;
     response1 = 3;
     response2 = 3;
     response3 = 3;
     group = 3;
     if f1 = 1 then response1 = 1;
     if f2 = 1 then response1 = 2;
     if m1 = 1 then response2 = 1;
     if m2 = 1 then response2 = 2;
     if d1 = 1 then response3 = 1;
     if d2 = 1 then response3 = 2;
     if g1 = 1 then group = 1;
     if g2 = 1 then group = 2;
     drop f1-f3 m1-m3 d1-d3;
run;


data DS3m.step2data3;
     set DS3m.step2data2;

if group=1 then
do;
   if response1=1 and response2=1 and response3=1 then  /*Cf means the
choice of father */
      do;
         Cf=1; Cm=1; Cd=1; conflict=0; flag=1;  output;
         Cf=2; Cm=1; Cd=1; conflict=1; flag=1;  output;
         Cf=1; Cm=2; Cd=1; conflict=1; flag=1;  output;
         Cf=1; Cm=1; Cd=2; conflict=1; flag=1;  output;

         Cf=1; Cm=2; Cd=2; conflict=1; flag=1;  output;
         Cf=2; Cm=1; Cd=2; conflict=1; flag=1;  output;
         Cf=2; Cm=2; Cd=1; conflict=1; flag=1;  output;
         /*Cf=2; Cm=2; Cd=2; is impossible.*/
       end;
```

```
if response1=1 and response2=1 and response3=3 then
  do;
    Cf=1; Cm=1; Cd=3; conflict=0; flag=2;  output;
    Cf=1; Cm=1; Cd=2; conflict=1; flag=2;  output;
    Cf=1; Cm=2; Cd=3; conflict=1; flag=2;  output;
    Cf=2; Cm=1; Cd=3; conflict=1; flag=2;  output;

    Cf=1; Cm=2; Cd=2; conflict=1; flag=2;  output;
    Cf=2; Cm=1; Cd=2; conflict=1; flag=2;  output;
    Cf=0; Cm=0; Cd=0; conflict=0; flag=2;  output;
    /*Cf=2; Cm=2; Cd=2; is impossible.*/
    /*Cf=2; Cm=2; Cd=3; is impossible.*/
  end;

if response1=1 and response2=3 and response3=1 then
  do;
    Cf=1; Cm=3; Cd=1; conflict=0; flag=3;  output;
    Cf=1; Cm=2; Cd=1; conflict=1; flag=3;  output;
    Cf=1; Cm=3; Cd=2; conflict=1; flag=3;  output;
    Cf=2; Cm=3; Cd=1; conflict=1; flag=3;  output;

    Cf=1; Cm=2; Cd=2; conflict=1; flag=3;  output;
    Cf=2; Cm=2; Cd=1; conflict=1; flag=3;  output;
    Cf=0; Cm=0; Cd=0; conflict=0; flag=3;  output;
    /*Cf=2; Cm=2; Cd=2; is impossible.*/
    /*Cf=2; Cm=3; Cd=2; is impossible.*/
  end;

if response1=3 and response2=1 and response3=1 then
  do;
    Cf=3; Cm=1; Cd=1; conflict=0; flag=4;  output;
    Cf=2; Cm=1; Cd=1; conflict=1; flag=4;  output;
    Cf=3; Cm=2; Cd=1; conflict=1; flag=4;  output;
    Cf=3; Cm=1; Cd=2; conflict=1; flag=4;  output;

    Cf=2; Cm=1; Cd=2; conflict=1; flag=4;  output;
    Cf=2; Cm=2; Cd=1; conflict=1; flag=4;  output;
    Cf=0; Cm=0; Cd=0; conflict=0; flag=4;  output;
   /*Cf=2; Cm=2; Cd=2; is impossible.*/
   /*Cf=3; Cm=2; Cd=2; is impossible.*/
   end;

if response1=1 and response2=3 and response3=3 then
  do;
    Cf=1; Cm=3; Cd=3; conflict=0; flag=0;  output;
    Cf=1; Cm=2; Cd=3; conflict=1; flag=0;  output;
    Cf=1; Cm=3; Cd=2; conflict=1; flag=0;  output;
    Cf=1; Cm=2; Cd=2; conflict=1; flag=0;  output;

    Cf=0; Cm=0; Cd=0; conflict=0; flag=0;  output;
    Cf=0; Cm=0; Cd=0; conflict=0; flag=0;  output;
    Cf=0; Cm=0; Cd=0; conflict=0; flag=0;  output;
    /*Cf=2; Cm=2; Cd=2; is impossible.*/
    /*Cf=2; Cm=3; Cd=3; is impossible.*/
    /*Cf=2; Cm=3; Cd=2; is impossible.*/
    /*Cf=2; Cm=2; Cd=3; is impossible.*/

   end;
if response1=3 and response2=1 and response3=3 then
  do;
```

```
      Cf=3; Cm=1; Cd=3; conflict=0; flag=5;  output;
      Cf=2; Cm=1; Cd=3; conflict=1; flag=5;  output;
      Cf=3; Cm=1; Cd=2; conflict=1; flag=5;  output;
      Cf=2; Cm=1; Cd=2; conflict=1; flag=5;  output;

      Cf=0; Cm=0; Cd=0; conflict=0; flag=5;  output;
      Cf=0; Cm=0; Cd=0; conflict=0; flag=5;  output;
      Cf=0; Cm=0; Cd=0; conflict=0; flag=5;  output;
      /*Cf=2; Cm=2; Cd=2; is impossible.*/
      /*Cf=2; Cm=2; Cd=3; is impossible.*/
      /*Cf=3; Cm=2; Cd-2; is impossible.*/
      /*Cf=3; Cm=2; Cd=3; is impossible.*/
     end;

  if response1=3 and response2=3 and response3=1 then
    do;
      Cf=3; Cm=3; Cd=1; conflict=0; flag=6;  output;
      Cf=3; Cm=2; Cd=1; conflict=1; flag=6;  output;
      Cf=2; Cm=3; Cd=1; conflict=1; flag=6;  output;
      Cf=2; Cm=2; Cd=1; conflict=1; flag=6;  output;

      Cf=0; Cm=0; Cd=0; conflict=0; flag=6;  output;
      Cf=0; Cm=0; Cd=0; conflict=0; flag=6;  output;
      Cf=0; Cm=0; Cd=0; conflict=0; flag=6;  output;
      /*Cf=2; Cm=2; Cd=2; is impossible.*/
      /*Cf=2; Cm=3; Cd=2; is impossible.*/
      /*Cf=3; Cm=2; Cd=2; is impossible.*/
      /*Cf=2; Cm=3; Cd=3; is impossible.*/
    end;

end;

*****************************************************************;

if group=2 then
do;
  if response1=2 and response2=2 and response3=2 then
    do;
      Cf=2; Cm=2; Cd=2; conflict=0; flag=7;  output;
      Cf=1; Cm=2; Cd=2; conflict=1; flag=7;  output;
      Cf=2; Cm=1; Cd=2; conflict=1; flag=7;  output;
      Cf=2; Cm=2; Cd=1; conflict=1; flag=7;  output;

      Cf=1; Cm=1; Cd=2; conflict=1; flag=7;  output;
      Cf=1; Cm=2; Cd=1; conflict=1; flag=7;  output;
      Cf=2; Cm=1; Cd=1; conflict=1; flag=7;  output;
     end;

  if response1=2 and response2=2 and response3=3 then
    do;
      Cf=2; Cm=2; Cd=3; conflict=0; flag=8;  output;
      Cf=2; Cm=2; Cd=1; conflict=1; flag=8;  output;
      Cf=2; Cm=1; Cd=3; conflict=1; flag=8;  output;
      Cf=1; Cm=2; Cd=3; conflict=1; flag=8;  output;

      Cf=1; Cm=2; Cd=1; conflict=1; flag=8;  output;
      Cf=2; Cm=1; Cd=1; conflict=1; flag=8;  output;

      Cf=0; Cm=0; Cd=0; conflict=0; flag=8;  output;

      /*Cf=1; Cm=1; Cd=1; is impossible.*/
```

```
    /*Cf=1; Cm=1; Cd=3; is impossible.*/
   end;

 if response1=2 and response2=3 and response3=2 then
   do;
     Cf=2; Cm=3; Cd=2; conflict=0; flag=9;  output;
     Cf=2; Cm=1; Cd=2; conflict=1; flag=9;  output;
     Cf=2; Cm=3; Cd=1; conflict=1; flag=9;  output;
     Cf=1; Cm=3; Cd=2; conflict=1; flag=9;  output;

     Cf=1; Cm=1; Cd=2; conflict=1; flag=9;  output;
     Cf=2; Cm=1; Cd=1; conflict=1; flag=9;  output;

     Cf=0; Cm=0; Cd=0; conflict=0; flag=9;  output;

     /*Cf=1; Cm=1; Cd=1; is impossible.*/
     /*Cf=1; Cm=3; Cd=1; is impossible.*/
   end;

 if response1=3 and response2=2 and response3-2 then
   do;
     Cf=3; Cm=2; Cd=2; conflict=0; flag=10;  output;
     Cf=1; Cm=2; Cd=2; conflict=1; flag=10;  output;
     Cf=3; Cm=1; Cd=2; conflict=1; flag=10;  output;
     Cf=3; Cm=2; Cd=1; conflict=1; flag=10;  output;

     Cf=1; Cm=1; Cd=2; conflict=1; flag=10;  output;
     Cf=1; Cm=2; Cd=1; conflict=1; flag=10;  output;

     Cf=0; Cm=0; Cd=0; conflict=0; flag=10;  output;

     /*Cf=1; Cm=1; Cd=1; is impossible.*/
     /*Cf=3; Cm=1; Cd=1; is impossible.*/
    end;

 if response1=2 and response2=3 and response3=3 then
    do;
     Cf=2; Cm=3; Cd=3; conflict=0; flag=11;  output;
     Cf=2; Cm=1; Cd=3; conflict=1; flag=11;  output;
     Cf=2; Cm=3; Cd=1; conflict=1; flag=11;  output;
     Cf=2; Cm=1; Cd=1; conflict=1; flag=11;  output;

     Cf=0; Cm=0; Cd=0; conflict=0; flag=11;  output;
     Cf=0; Cm=0; Cd=0; conflict=0; flag=11;  output;
     Cf=0; Cm=0; Cd=0; conflict=0; flag=11;  output;

    /*Cf=1; Cm=1; Cd=1; is impossible.*/
    /*Cf=1; Cm=1; Cd=3; is impossible.*/
    /*Cf=1; Cm=3; Cd=1; is impossible.*/
    /*Cf=1; Cm=3; Cd=3; is impossible.*/
    end;
 if response1=3 and response2=2 and response3=3 then
    do;
     Cf=3; Cm=2; Cd=3; conflict=0; flag=12;   output;
     Cf=1; Cm=2; Cd=3; conflict=1; flag=12;   output;
     Cf=3; Cm=2; Cd=1; conflict=1; flag=12;   output;
     Cf=1; Cm=2; Cd=1; conflict=1; flag=12;   output;

     Cf=0; Cm=0; Cd=0; conflict=0; flag=12;  output;
     Cf=0; Cm=0; Cd=0; conflict=0; flag=12;  output;
     Cf=0; Cm=0; Cd=0; conflict=0; flag=12;  output;
```

```
      /*Cf=1; Cm=1; Cd=1; is impossible.*/
      /*Cf=1; Cm=1; Cd=3; is impossible.*/
      /*Cf=3; Cm=1; Cd=1; is impossible.*/
      /*Cf=3; Cm=1; Cd=3; is impossible.*/
     end;

  if response1=3 and response2=3 and response3=2 then
     do;
       Cf=3; Cm=3; Cd=2; conflict=0; flag=13;  output;
       Cf=3; Cm=1; Cd=2; conflict=1; flag=13;  output;
       Cf=1; Cm=3; Cd=2; conflict=1; flag=13;  output;
       Cf=1; Cm=1; Cd=2; conflict=1; flag=13;  output;

       Cf=0; Cm=0; Cd=0; conflict=0; flag=13;  output;
       Cf=0; Cm=0; Cd=0; conflict=0; flag=13;  output;
       Cf=0; Cm=0; Cd=0; conflict=0; flag=13;  output;

       /*Cf=1; Cm=1; Cd=1; is impossible.*/
       /*Cf=1; Cm=3; Cd=1; is impossible.*/
       /*Cf=3; Cm=1; Cd=1; is impossible.*/
       /*Cf=3; Cm=3; Cd=1; is impossible.*/
      end;
  end;
*****************************************************************;
  if group=3 then
   do;
      Cf=3; Cm=3; Cd=3; conflict=0; flag=99;  output;

        Cf=0; Cm=0; Cd=0; conflict=0; flag=99;  output;
      Cf=0; Cm=0; Cd=0; conflict=0; flag=99;  output;
       Cf=0; Cm=0; Cd=0; conflict=0; flag=99;  output;
        Cf=0; Cm=0; Cd=0; conflict=0; flag=99;  output;
        Cf=0; Cm=0; Cd=0; conflict=0; flag=99;  output;
       Cf=0; Cm=0; Cd=0; conflict=0; flag=99;  output;

   end;
run;
*****************************************************************;
data DS3m.step2data4;
    set DS3m.step2data3;
    array choicef(3);
    array choicem(3);
    array choiced(3);
    do i=1 to 3;
        choicef(i)=0;
        choicem(i)=0;
        choiced(i)=0;
    end;
    if Cf^=0 and Cm^=0 and Cd^=0 then
    do;
        choicef(Cf)=1;
        choicem(Cm)=1;
        choiced(Cd)=1;
    end;
run;
*****************************************************************;
proc sql;
    create table DS3m.step2data5 as
    select /*1-7*/date, slot,
tvbcode,allslot1,cntslot1,allday1,cntday1,
```

```
/*8-12*/atvcode,allslot2,cntslot2,allday2,cntday2,
                          /*13-20*/SB1, SB2, SE1, SE2, B1, B2, E1,
E2,tvbslot, atvslot,
                          /*23-25*/fptvb, fpatv, fnowatch,
                          /*26-28*/mptvb, mpatv, mnowatch,
                          /*29-31*/dptvb, dpatv, dnowatch,
                          /*32-34*/choicef1,choicef2,choicef3,
                          /*35-37*/choicem1,choicem2,choicem3,
                          /*38-40*/choiced1,choiced2,choiced3,
                          /*41-43*/g1,g2,g3,

     /*44-49*/Sftvb1,Sftvb2,Sftvb3,Sfatv1,Sfatv2,Sfatv3,

     /*50-55*/Smtvb1,Smtvb2,Smtvb3,Smatv1,Smatv2,Smatv3,

     /*56-61*/Sdtvb1,Sdtvb2,Sdtvb3,Sdatv1,Sdatv2,Sdatv3,
                            /*62-63*/DTVB,DATV,
                            /*64-65*/conflict,flag
     from DS3m.step2data4;
quit;

*******************************************************************;
/* Step II - IML I*/
proc iml;
     use DS3m.step2data5;
     read all into data;
     use DS3m.imlstep1;
     read all into input;
     /*
          u:1-7:tvb, 8-14:atv
          data:15-21, 22-28
          alpha:29-49:tvb, 50-70:atv
          beta:71-74
          gamma:75-76
          k1:77
     */
     Start maxFunc1(W) global(data,input) ;
          *NUM = 35;
          NUM = nrow(data);
          tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
          atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
          Vh=J(1,2,0);
          prob=0;
          sum = 0;

          do i = 1 to (NUM/7);
               prob=0;
                    z = (i-1)*7+1;
                    tvbcode = data[z,3];
                    tvbtype = tvb_type[tvbcode];
                    atvcode = data[z,8];
                    atvtype = atv_type[atvcode];

                    Uf1 = data[z,62]*input[1,tvbtype] +
(1-data[z,62])*(input[1,14+tvbtype] +
input[1,28+(tvbtype-1)*3+1]*data[z,44] +
input[1,28+(tvbtype-1)*3+2]*data[z,45] +
input[1,28+(tvbtype-1)*3+3]*data[z,46])
                         +
input[1,71]*data[z,17]+input[1,72]*data[z,18]+input[1,73]*data[z,19]+
```

```
input[1,74]*data[z,20]+input[1,75]*data[z,13]+input[1,76]*data[z,15];
                  Uf2 = data[z,63]*input[1,7+atvtype] +
(1-data[z,63])*(input[1,21+atvtype] +
input[1,49+(atvtype-1)*3+1]*data[z,47] +
input[1,49+(atvtype-1)*3+2]*data[z,48] +
input[1,49+(atvtype-1)*3+3]*data[z,49])
                       +
input[1,71]*data[z,17]+input[1,72]*data[z,18]+input[1,73]*data[z,19]+
input[1,74]*data[z,20]+input[1,75]*data[z,14]+input[1,76]*data[z,16];

                  Um1 = data[z,62]*input[2,tvbtype] +
(1-data[z,62])*(input[2,14+tvbtype] +
input[2,28+(tvbtype-1)*3+1]*data[z,50] +
input[2,28+(tvbtype-1)*3+2]*data[z,51] +
input[2,28+(tvbtype-1)*3+3]*data[z,52])
                       +
input[2,71]*data[z,17]+input[2,72]*data[z,18]+input[2,73]*data[z,19]+
input[2,74]*data[z,20]+input[2,75]*data[z,13]+input[2,76]*data[z,15];
                  Um2 = data[z,63]*input[2,7+atvtype] +
(1-data[z,63])*(input[2,21+atvtype] +
input[2,49+(atvtype-1)*3+1]*data[z,53] +
input[2,49+(atvtype-1)*3+2]*data[z,54] +
input[2,49+(atvtype-1)*3+3]*data[z,55])
                       +
input[2,71]*data[z,17]+input[2,72]*data[z,18]+input[2,73]*data[z,19]+
input[2,74]*data[z,20]+input[2,75]*data[z,14]+input[2,76]*data[z,16];


                  Ud1 = data[z,62]*input[3,tvbtype] +
(1-data[z,62])*(input[3,14+tvbtype] +
input[3,28+(tvbtype-1)*3+1]*data[z,56] +
input[3,28+(tvbtype-1)*3+2]*data[z,57] +
input[3,28+(tvbtype-1)*3+3]*data[z,58])
                       +
input[3,71]*data[z,17]+input[3,72]*data[z,18]+input[3,73]*data[z,19]+
input[3,74]*data[z,20]+input[3,75]*data[z,13]+input[3,76]*data[z,15];
                  Ud2 = data[z,63]*input[3,7+atvtype] +
(1-data[z,63])*(input[3,21+atvtype] +
input[3,49+(atvtype-1)*3+1]*data[z,59] +
input[3,49+(atvtype-1)*3+2]*data[z,60] +
input[3,49+(atvtype-1)*3+3]*data[z,61])
                       +
input[3,71]*data[z,17]+input[3,72]*data[z,18]+input[3,73]*data[z,19]+
input[3,74]*data[z,20]+input[3,75]*data[z,14]+input[3,76]*data[z,16];

                  Pf1 = exp(Uf1)/(exp(Uf1)+exp(Uf2)+exp(input[1,77]));
                  Pf2 = exp(Uf2)/(exp(Uf1)+exp(Uf2)+exp(input[1,77]));
                  Pf3 =
exp(input[1,77])/(exp(Uf1)+exp(Uf2)+exp(input[1,77]));
                  Pm1 = exp(Um1)/(exp(Um1)+exp(Um2)+exp(input[2,77]));
                  Pm2 = exp(Um2)/(exp(Um1)+exp(Um2)+exp(input[2,77]));
                  Pm3 =
exp(input[2,77])/(exp(Um1)+exp(Um2)+exp(input[2,77]));
                  Pd1 = exp(Ud1)/(exp(Ud1)+exp(Ud2)+exp(input[3,77]));
                  Pd2 = exp(Ud2)/(exp(Ud1)+exp(Ud2)+exp(input[3,77]));
                  Pd3 =
exp(input[3,77])/(exp(Ud1)+exp(Ud2)+exp(input[3,77]));
              do j = 1 to 7;
                  z = (i-1)*7+j;
                  /* step1*/
                  Prof=Pf1*data[z,32]+Pf2*data[z,33]+Pf3*data[z,34];
```

```
                Prom=Pm1*data[z,35]+Pm2*data[z,36]+Pm3*data[z,37];
                Prod=Pd1*data[z,38]+Pd2*data[z,39]+Pd3*data[z,40];

    ******************************************************************;
                /* step2 */
                /* interaction: fm fd md*/

    Vh[1]=W[1]*data[z,32]+W[2]*data[z,35]+W[3]*data[z,38]+W[4]*data[z
,32]*data[z,35]+W[5]*data[z,32]*data[z,38]+W[6]*data[z,35]*data[z,38]
;

    Vh[2]=W[1]*data[z,33]+W[2]*data[z,36]+W[3]*data[z,39]+W[4]*data[z
,33]*data[z,36]+W[5]*data[z,33]*data[z,39]+W[6]*data[z,36]*data[z,39]
;
                duta1 = exp(Vh[1])/(exp(Vh[1])+exp(Vh[2])) ;
                duta2 = exp(Vh[2])/(exp(Vh[1])+exp(Vh[2])) ;
                duta3 = 1;
                group1 = (duta1*data[z,41] + duta2*data[z,42] +
duta3*data[z,43]) ** data[z,64];

                prob = prob + (Prof*Prom*Prod)*group1;
            end;/* End of j */
            sum = sum + log(prob) ;
        end;/* End of i */
        return (sum);
    Finish maxFunc1;

    optn={1 2};
    X = J(1,6,0);
    con = J(2,8,.);
    con[1,1:6] = -5;
    con[2,1:6] = +5;
    tc = repeat(.,12);
    tc[1] = 4;
    tc[2] = 10;

    call nlpcg(rc,xres,"maxFunc1",X,optn,con,tc);
    Create DS3m.imlstep2_1 from xres ;
    Append from xres ;
quit;


*****************************************************************;
/* Step II - IML II*/
proc iml;
    use DS3m.step2data5;
    read all into data;
    use DS3m.imlstep1;
    read all into input;
    use DS3m.imlstep2_1;
    read all into weight;
    /*
        u:1-7:tvb, 8-14:atv
        duta:15-21, 22-28
        alpha:29-49:tvb, 50-70:atv
        beta:71-74
        gamma:75-76
        k1:77
    */
    Start maxFunc1(F) global(data,input) ;
        *NUM = 35;
```

```
        NUM = nrow(data);
        tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
        atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
        Vh=J(1,2,0);
        prob=0;
        sum = 0;

        do i = 1 to (NUM/7);
             prob=0;
                  z = (i-1)*7+1;
                  tvbcode = data[z,3];
                  tvbtype = tvb_type[tvbcode];
                  atvcode = data[z,8];
                  atvtype = atv_type[atvcode];

                  Uf1 = data[z,62]*F[77*0+tvbtype] +
(1-data[z,62])*(F[77*0+14+tvbtype] +
F[77*0+28+(tvbtype-1)*3+1]*data[z,44] +
F[77*0+28+(tvbtype-1)*3+2]*data[z,45] +
F[77*0+28+(tvbtype-1)*3+3]*data[z,46])
                        +
F[77*0+71]*data[z,17]+F[77*0+72]*data[z,18]+F[77*0+73]*data[z,19]+F[7
7*0+74]*data[z,20]+F[77*0+75]*data[z,13]+F[77*0+76]*data[z,15];
                  Uf2 = data[z,63]*F[77*0+7+atvtype] +
(1-data[z,63])*(F[77*0+21+atvtype] +
F[77*0+49+(atvtype-1)*3+1]*data[z,47] +
F[77*0+49+(atvtype-1)*3+2]*data[z,48] +
F[77*0+49+(atvtype-1)*3+3]*data[z,49])
                        +
F[77*0+71]*data[z,17]+F[77*0+72]*data[z,18]+F[77*0+73]*data[z,19]+F[7
7*0+74]*data[z,20]+F[77*0+75]*data[z,14]+F[77*0+76]*data[z,16];

                  Um1 = data[z,62]*F[77*1+tvbtype] +
(1-data[z,62])*(F[77*1+14+tvbtype] +
F[77*1+28+(tvbtype-1)*3+1]*data[z,50] +
F[77*1+28+(tvbtype-1)*3+2]*data[z,51] +
F[77*1+28+(tvbtype-1)*3+3]*data[z,52])
                        +
F[77*1+71]*data[z,17]+F[77*1+72]*data[z,18]+F[77*1+73]*data[z,19]+F[7
7*1+74]*data[z,20]+F[77*1+75]*data[z,13]+F[77*1+76]*data[z,15];
                  Um2 = data[z,63]*F[77*1+7+atvtype] +
(1-data[z,63])*(F[77*1+21+atvtype] +
F[77*1+49+(atvtype-1)*3+1]*data[z,53] +
F[77*1+49+(atvtype-1)*3+2]*data[z,54] +
F[77*1+49+(atvtype-1)*3+3]*data[z,55])
                        +
F[77*1+71]*data[z,17]+F[77*1+72]*data[z,18]+F[77*1+73]*data[z,19]+F[7
7*1+74]*data[z,20]+F[77*1+75]*data[z,14]+F[77*1+76]*data[z,16];


                  Ud1 = data[z,62]*F[77*2+tvbtype] +
(1-data[z,62])*(F[77*2+14+tvbtype] +
F[77*2+28+(tvbtype-1)*3+1]*data[z,56] +
F[77*2+28+(tvbtype-1)*3+2]*data[z,57] +
F[77*2+28+(tvbtype-1)*3+3]*data[z,58])
                        +
F[77*2+71]*data[z,17]+F[77*2+72]*data[z,18]+F[77*2+73]*data[z,19]+F[7
7*2+74]*data[z,20]+F[77*2+75]*data[z,13]+F[77*2+76]*data[z,15];
                  Ud2 = data[z,63]*F[77*2+7+atvtype] +
(1-data[z,63])*(F[77*2+21+atvtype] +
F[77*2+49+(atvtype-1)*3+1]*data[z,59] +
```

```
F[77*2+49+(atvtype-1)*3+2]*data[z,60] +
F[77*2+49+(atvtype-1)*3+3]*data[z,61])
                    +
F[77*2+71]*data[z,17]+F[77*2+72]*data[z,18]+F[77*2+73]*data[z,19]+F[7
7*2+74]*data[z,20]+F[77*2+75]*data[z,14]+F[77*2+76]*data[z,16];


                Pf1 = exp(Uf1)/(exp(Uf1)+exp(Uf2)+exp(F[1*77]));
                Pf2 = exp(Uf2)/(exp(Uf1)+exp(Uf2)+exp(F[1*77]));
                Pf3 = exp(F[1*77])/(exp(Uf1)+exp(Uf2)+exp(F[1*77]));
                Pm1 = exp(Um1)/(exp(Um1)+exp(Um2)+exp(F[2*77]));
                Pm2 = exp(Um2)/(exp(Um1)+exp(Um2)+exp(F[2*77]));
                Pm3 = exp(F[2*77])/(exp(Um1)+exp(Um2)+exp(F[2*77]));
                Pd1 = exp(Ud1)/(exp(Ud1)+exp(Ud2)+exp(F[3*77]));
                Pd2 = exp(Ud2)/(exp(Ud1)+exp(Ud2)+exp(F[3*77]));
                Pd3 = exp(F[3*77])/(exp(Ud1)+exp(Ud2)+exp(F[3*77]));
            do j = 1 to 7;
                z = (i-1)*7+j;
                /* step1*/
                Prof=Pf1*data[z,32]+Pf2*data[z,33]+Pf3*data[z,34];
                Prom=Pm1*data[z,35]+Pm2*data[z,36]+Pm3*data[z,37];
                Prod=Pd1*data[z,38]+Pd2*data[z,39]+Pd3*data[z,40];

    ***************************************************************;
                /* step2 */
                /* interaction: fm fd fs md ms ds */

    Vh[1]=F[232]*data[z,32]+F[233]*data[z,35]+F[234]*data[z,38]+F[235
]*data[z,32]*data[z,35]+F[236]*data[z,32]*data[z,38]+F[237]*data[z,35
]*data[z,38];

    Vh[2]=F[232]*data[z,33]+F[233]*data[z,36]+F[234]*data[z,39]+F[235
]*data[z,33]*data[z,36]+F[236]*data[z,33]*data[z,39]+F[237]*data[z,36
]*data[z,39];
                duta1 = exp(Vh[1])/(exp(Vh[1])+exp(Vh[2])) ;
                duta2 = exp(Vh[2])/(exp(Vh[1])+exp(Vh[2])) ;
                duta3 = 1;
                group1 = (duta1*data[z,41] + duta2*data[z,42] +
duta3*data[z,43]) ** data[z,64];

                prob = prob + (Prof*Prom*Prod)*group1;
            end;/* End of j */
            sum = sum + log(prob) ;
        end;/* End of i */
        return (sum);
    Finish maxFunc1;
    optn={1 2};
    X = J(1,237,0);
    do i = 1 to 77;
        X[77*0+i] = input[1,i];
        X[77*1+i] = input[2,i];
        X[77*2+i] = input[3,i];
    end;

    X[232:237] = weight[1:6];
    con = J(2,239,.);
    con[1,1:237] = 0;
    con[2,1:237] = 1;
    do i = 1 to 14;
        con[1,77*0+i] = -5;
        con[1,77*1+i] = -5;
```

```
        con[1,77*2+i] = -5;
        con[2,77*0+i] = +5;
        con[2,77*1+i] = +5;
        con[2,77*2+i] = +5;
    end;

    con[1,232:237] = -5;
    con[2,232:237] = +5;

    tc = repeat(.,12);
    tc[1] = 4;
    tc[2] = 10;

    call nlpcg(rc,xres,"maxFunc1",X,optn,con,tc);
    Create DS3m.imlstep2_2 from xres ;
    Append from xres ;
quit;


/*****************************************************************
**********************/
/* Evaluation */

data DS3m.step2eva0;
     set DS3m.step1eva2;
     array w{6}(6*0);
run;

proc iml;
     use DS3m.imlstep2_2;
     read all into par1;

     use DS3m.step2eva0;
     read all into data;

     par = J(4,77,0);
     par[1,1:77] = par1[1,1:77];
     par[2,1:77] = par1[1,78:154];
     par[3,1:77] = par1[1,155:231];
     /*
          u:1-7:tvb, 8-14:atv
          duta:15-21, 22-28
          alpha:29-49:tvb, 50-70:atv
          beta:71-74
          gamma:75-76
          k1:77
      */
      tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
      atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
 /*
           1-2:date slot
           3-7:tvbcode allslot1 cntslot1 allday1 cntday1
           8-12:atvcode allslot2 cntslot2 allday2 cntday2
           13-22:SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
           23-26:response1 response2 response3  group
           27-30:eresponse1 eresponse2 eresponse3 egroup
           31-39:ep1tvbu ep1atvu ek1 ep2tvbu ep2atvu ek2 ep3tvbu ep3atvu
 ek3
           40-51:ef1-3, em1-3, ed1-3,eg1-3,
           52-57:w1-w6
 */
```

```
   do i = 1 to nrow(data);
        data[i,33] = par[1,77];
        data[i,36] = par[2,77];
        data[i,39] = par[3,77];
        data[i,52:57] = par1[1,232:237];
   end;
   do i = 1 to nrow(data);
        if data[i,7]  < 4 then
        do;
             tvbcode = data[i,3];
             tvbtype = tvb_type[tvbcode];
             data[i,31] = par[1,tvbtype] + par[1,71]*data[i,17] +
par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
par[1,75]*data[i,13] + par[1,76]*data[i,15];
             data[i,34] = par[2,tvbtype] + par[2,71]*data[i,17] +
par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
par[2,75]*data[i,13] + par[2,76]*data[i,15];
             data[i,37] = par[3,tvbtype] + par[3,71]*data[i,17] +
par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
par[3,75]*data[i,13] + par[3,76]*data[i,15];
        end;
        if data[i,12] < 4 then
        do;
             atvcode = data[i,8];
             atvtype = atv_type[atvcode];
             data[i,32] = par[1,7+atvtype] + par[1,71]*data[i,17] +
par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
par[1,75]*data[i,14] + par[1,76]*data[i,16];
             data[i,35] = par[2,7+atvtype] + par[2,71]*data[i,17] +
par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
par[2,75]*data[i,14] + par[2,76]*data[i,16];
             data[i,38] = par[3,7+atvtype] + par[3,71]*data[i,17] +
par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
par[3,75]*data[i,14] + par[3,76]*data[i,16];
        end;
   end;

   create DS3m.step2eval var{
        date slot
        tvbcode allslot1 cntslot1 allday1 cntday1
        atvcode allslot2 cntslot2 allday2 cntday2
        SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
        response1 response2 response3 group
        eresponse1 eresponse2 eresponse3 egroup
        ep1tvbu ep1atvu ek1 ep2tvbu ep2atvu ek2 ep3tvbu ep3atvu ek3
        ef1 ef2 ef3 em1 em2 em3 ed1 ed2 ed3 eg1 eg2 eg3
        w1 w2 w3 w4 w5 w6
        };
   append from data;
quit;

data DS3m.step2eva2;
   set DS3m.step2eval;
   if cntday1 < 4 & cntday2 < 4 then
   do;
        if ep1tvbu > ep1atvu & 2*ep1tvbu + ep1atvu > 1 then do;ef1 =
1;ef3=0;end;
        if ep1atvu > ep1tvbu & 2*ep1atvu + ep1tvbu > 1 then do;ef2 =
1;ef3=0;end;
        if ep2tvbu > ep2atvu & 2*ep2tvbu + ep2atvu > 1 then do;em1 =
```

```
1;em3=0;end;
        if ep2atvu > ep2tvbu & 2*ep2atvu + ep2tvbu > 1 then do;em2 =
1;em3=0;end;
        if ep3tvbu > ep3atvu & 2*ep3tvbu + ep3atvu > 1 then do;ed1 =
1;ed3=0;end;
        if ep3atvu > ep3tvbu & 2*ep3atvu + ep3tvbu > 1 then do;ed2 =
1;ed3=0;end;
    end;
run;

proc iml;
    use DS3m.step2eva2;
    read all into data;

    use DS3m.imlstep2_2;
    read all into par1;

    par = J(4,77,0);
    par[1,1:77] = par1[1,1:77];
    par[2,1:77] = par1[1,78:154];
    par[3,1:77] = par1[1,155:231];

    Sf = J(1,3,0);
    Sm = J(1,3,0);
    Sd = J(1,3,0);
    tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
    atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
/*
        1-2:date slot
        3-7:tvbcode allslot1 cntslot1 allday1 cntday1
        8-12:atvcode allslot2 cntslot2 allday2 cntday2
        13-22:SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
        23-26:response1 response2 response3  group
        27-30:eresponse1 eresponse2 eresponse3 egroup
        31-39:ep1tvbu ep1atvu ek1 ep2tvbu ep2atvu ek2 ep3tvbu ep3atvu
ek3
        40-51:ef1-3, em1-3, ed1-3,eg1-3,
        52-57:w1-w6
*/

    do i = 1 to nrow(data);
        if data[i,7] >= 4 then
        do;
            tvbcode = data[i,3];
            tvbtype = tvb_type[tvbcode];
            counter = 0;
            date = data[i,1];
            Sf[1:3] = 0;Sm[1:3] = 0;Sd[1:3] = 0;
            do j = 1 to 100;
                k  = i - j;
                if k < 1 then goto position1;
                if data[k,3] = tvbcode then
                    if data[k,1] < data[i,1] then
                        do;
                            if data[k,1] < date then
                                do;
                                    counter = counter + 1;
                                    date = data[k,1];
                                end;
                            if counter = 4 then goto position1;
                            Sf[counter] =
```

```
Sf[counter]+data[i,40]/data[i,21];
                                   Sm[counter] =
Sm[counter]+data[i,43]/data[i,21];
                                   Sd[counter] =
Sd[counter]+data[i,46]/data[i,21];
                               end;
                 end;
                 position1:
                 data[i,31] = par[1,14+tvbtype] + par[1,71]*data[i,17] +
par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
par[1,75]*data[i,13] + par[1,76]*data[i,15];
                 data[i,34] = par[2,14+tvbtype] + par[2,71]*data[i,17] +
par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
par[2,75]*data[i,13] + par[2,76]*data[i,15];
                 data[i,37] = par[3,14+tvbtype] + par[3,71]*data[i,17] +
par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
par[3,75]*data[i,13] + par[3,76]*data[i,15];
                 data[i,31] = data[i,31] +
Sf[1]*par[1,28+(tvbtype-1)*3+1] + Sf[2]*par[1,28+(tvbtype-1)*3+2]  +
Sf[3]*par[1,28+(tvbtype-1)*3+3] ;
                 data[i,34] = data[i,34] +
Sm[1]*par[2,28+(tvbtype-1)*3+1] + Sm[2]*par[2,28+(tvbtype-1)*3+2]  +
Sm[3]*par[2,28+(tvbtype-1)*3+3] ;
                 data[i,37] = data[i,37] +
Sd[1]*par[3,28+(tvbtype-1)*3+1] + Sd[2]*par[3,28+(tvbtype-1)*3+2]  +
Sd[3]*par[3,28+(tvbtype-1)*3+3] ;
         end;
         if data[i,12] >= 4 then
         do;
              atvcode = data[i,8];
              atvtype = atv_type[atvcode];
              counter = 0;
              date = data[i,1];
              Sf[1:3] = 0;Sm[1:3] = 0;Sd[1:3] = 0;
                   do j = 1 to 100;
                        k  = i - j;
                        if k < 1 then goto position2;
                        if data[k,8] = atvcode then
                             if data[k,1] < data[i,1] then
                                  do;
                                       if data[k,1] < date then
                                            do;
                                                 counter = counter + 1;
                                                 date = data[k,1];
                                            end;
                                       if counter = 4 then goto position2;
                                       Sf[counter] =
Sf[counter]+data[i,41]/data[i,22];
                                       Sm[counter] =
Sm[counter]+data[i,44]/data[i,22];
                                       Sd[counter] =
Sd[counter]+data[i,47]/data[i,22];
                                  end;
                   end;
                   position2:
                   atvcode = data[i,8];
                   atvtype = atv_type[atvcode];
                   data[i,32] = par[1,21+atvcode] + par[1,71]*data[i,17] +
par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
par[1,75]*data[i,14] + par[1,76]*data[i,16];
                   data[i,35] = par[2,21+atvcode] + par[2,71]*data[i,17] +
```

```
par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
par[2,75]*data[i,14] + par[2,76]*data[i,16];
                    data[i,38] = par[3,21+atvcode] + par[3,71]*data[i,17] +
par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
par[3,75]*data[i,14] + par[3,76]*data[i,16];
                    data[i,32] = data[i,32] +
Sf[1]*par[1,49+(atvtype-1)*3+1] + Sf[2]*par[1,49+(atvtype-1)*3+2] +
Sf[3]*par[1,49+(atvtype-1)*3+3];
                    data[i,35] = data[i,35] +
Sm[1]*par[2,49+(atvtype-1)*3+1] + Sm[2]*par[2,49+(atvtype-1)*3+2] +
Sm[3]*par[2,49+(atvtype-1)*3+3];
                    data[i,38] = data[i,38] +
Sd[1]*par[3,49+(atvtype-1)*3+1] + Sd[2]*par[3,49+(atvtype-1)*3+2] +
Sd[3]*par[3,49+(atvtype-1)*3+3];
          end;

          if data[i,12] >= 4 | data[i,7] >= 4 then
          do;
               if data[i,31] > data[i,32] & 2*data[i,31] + data[i,32] > 1
then do;data[i,40] = 1; data[i,42]=0;end;
               if data[i,32] > data[i,31] & 2*data[i,32] + data[i,31] > 1
then do;data[i,41] = 1; data[i,42]=0;end;
               if data[i,34] > data[i,35] & 2*data[i,34] + data[i,35] > 1
then do;data[i,43] = 1; data[i,45]=0;end;
               if data[i,35] > data[i,34] & 2*data[i,35] + data[i,34] > 1
then do;data[i,44] = 1; data[i,45]=0;end;
               if data[i,37] > data[i,38] & 2*data[i,37] + data[i,38] > 1
then do;data[i,46] = 1; data[i,48]=0;end;
               if data[i,38] > data[i,37] & 2*data[i,38] + data[i,37] > 1
then do;data[i,47] = 1; data[i,48]=0;end;
          end;
     end;
     create DS3m.step2eva3 var{
          date slot
          tvbcode allslot1 cntslot1 allday1 cntday1
          atvcode allslot2 cntslot2 allday2 cntday2
          SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
          response1 response2 response3 group
          eresponse1 eresponse2 eresponse3 egroup
          ep1tvbu ep1atvu k1 ep2tvbu ep2atvu k2 ep3tvbu ep3atvu k3
          ef1 ef2 ef3 em1 em2 em3 ed1 ed2 ed3 eg1 eg2 eg3
          w1 w2 w3 w4 w5 w6
         };
     append from data;
quit;

data DS3m.step2eva4;
     set DS3m.step2eva3;
     if ef1 = 1 then ef = 1;
     if ef2 = 1 then ef = 2;
     if ef3 = 1 then ef = 3;
     if em1 = 1 then em = 1;
     if em2 = 1 then em = 2;
     if em3 = 1 then em = 3;
     if ed1 = 1 then ed = 1;
     if ed2 = 1 then ed = 2;
     if ed3 = 1 then ed = 3;
run;

data DS3m.step2eva5;
     set DS3m.step2eva4;
```

```
 p1v1 = 0;
 p1v2 = 0;
 if ef = 1 then p1v1 = 1;
 if ef = 2 then p1v2 = 1;
 p2v1 = 0;
 p2v2 = 0;
 if em = 1 then p2v1 = 1;
 if em = 2 then p2v2 = 1;
 p3v1 = 0;
 p3v2 = 0;
 if ed = 1 then p3v1 = 1;
 if ed = 2 then p3v2 = 1;

vote1 = w1*p1v1 + w2*p2v1 + w3*p3v1 + w4*p1v1*p2v1 + w5*p1v1*p3v1  +
w6*p2v1*p3v1;
vote2 = w1*p1v2 + w2*p2v2 + w3*p3v2 + w4*p1v2*p2v2 + w5*p1v2*p3v2  +
w6*p2v2*p3v2;

if vote1 = 0 and vote2 = 0 then
do;
      egroup = 3;
      eresponse1 = 3;
      eresponse2 = 3;
      eresponse3 = 3;
end;
if vote1 = 0 and vote2 ^= 0 then egroup = 2;
if vote1 ^= 0 and vote2 = 0 then egroup = 1;
if vote1 ^= 0 and vote2 ^= 0 then
do;
      egroup1 = exp(vote1) / ( exp(vote1) + exp(vote2) );
      ran = ranuni(117);
      if ran < egroup1 then egroup = 1;
      else egroup = 2 ;
end;

if ( egroup = 1 ) and ( ef = 1) then eresponse1 = 1 ;
if ( egroup = 1 ) and ( em = 1) then eresponse2 = 1 ;
if ( egroup = 1 ) and ( ed = 1) then eresponse3 = 1 ;

if ( egroup = 1 ) and ( ef = 3) then eresponse1 = 3 ;
if ( egroup = 1 ) and ( em = 3) then eresponse2 = 3 ;
if ( egroup = 1 ) and ( ed = 3) then eresponse3 = 3 ;

if ( egroup = 2 ) and ( ef = 2) then eresponse1 = 2 ;
if ( egroup = 2 ) and ( em = 2) then eresponse2 = 2 ;
if ( egroup = 2 ) and ( ed = 2) then eresponse3 = 2 ;

if ( egroup = 2 ) and ( ef = 3) then eresponse1 = 3 ;
if ( egroup = 2 ) and ( em = 3) then eresponse2 = 3 ;
if ( egroup = 2 ) and ( ed = 3) then eresponse3 = 3 ;

  if (egroup = 1) and (ef = 2 ) then
   do  ;
       switch = exp(ep1tvbu) / ( exp(ep1tvbu)  + exp(k1) );
       ran = ranuni(118) ;
      if ran < switch then eresponse1 = 1 ;
       else eresponse1 = 3 ;
   end ;

  if (egroup = 1) and (em = 2 ) then
```

```
   do  ;
      switch = exp(ep2tvbu) / ( exp(ep2tvbu)  + exp(k2) );
      ran = ranuni(119) ;
     if ran < switch then eresponse2 = 1 ;
      else eresponse2 = 3 ;
   end ;

   if (egroup = 1) and (ed = 2 ) then
   do  ;
      switch = exp(ep3tvbu) / ( exp(ep3tvbu)  + exp(k3) );
      ran = ranuni(120) ;
     if ran < switch then eresponse3 = 1 ;
      else eresponse3 = 3 ;
   end ;

  if (egroup = 2) and (ef = 1 ) then
   do  ;
      switch = exp(ep1atvu) / ( exp(ep1atvu)  + exp(k1) );
      ran = ranuni(122) ;
     if ran < switch then eresponse1 = 2 ;
      else eresponse1 = 3 ;
   end ;

  if (egroup = 2) and (em = 1 ) then
   do  ;
      switch = exp(ep2atvu) / ( exp(ep2atvu)  + exp(k2) );
      ran = ranuni(123) ;
     if ran < switch then eresponse2 = 2 ;
      else eresponse2 = 3 ;
   end ;

   if (egroup = 2 ) and (ed = 1 ) then
   do  ;
      switch = exp(ep3atvu) / ( exp(ep3atvu)  + exp(k3) );
      ran = ranuni(124) ;
     if ran < switch then eresponse3 = 2 ;
      else eresponse3 = 3 ;
   end ;
run;

*************************************************************;

data DS3m.h2(keep=date slot group egroup response1 response2 response3
eresponse1 eresponse2 eresponse3 );
   set DS3m.step2eva5;
run;
*************************************************************;
proc freq data = DS3m.h2;
  tables group * egroup / chisq;

   tables response1 * eresponse1 / chisq;
   tables response2 * eresponse2 / chisq;
   tables response3 * eresponse3 / chisq;
run;


*************************************************************;
*************************************************************;


data DS3m.step3data1;
```

```
set DS3m.step2data4;
array switchf(7);
array switchm(7);
array switchd(7);

do i=1 to 7;
   switchf(i)=0;
   switchm(i)=0;
   switchd(i)=0;
end;

if group=1 then
do;
    if response1=1 and Cf=1
       then switchf(1)=1;
    if response1=1 and Cf=2
       then switchf(2)=1;
     if response1=3 and Cf=2
       then switchf(3)=1;

     if response2=1 and Cm=1
       then switchm(1)=1;
    if response2=1 and Cm=2
       then switchm(2)=1;
     if response2=3 and Cm=2
       then switchm(3)=1;

     if response3=1 and Cd=1
       then switchd(1)=1;
    if response3=1 and Cd=2
       then switchd(2)=1;
     if response3=3 and Cd=2
       then switchd(3)=1;
end;

if group=2 then
do;
     if response1=2 and Cf=1
       then switchf(4)=1;
     if response1=2 and Cf=2
       then switchf(5)=1;
     if response1=3 and Cf=1
       then switchf(6)=1;

     if response2=2 and Cm=1
       then switchm(4)=1;
     if response2=2 and Cm=2
       then switchm(5)=1;
     if response2=3 and Cm=1
       then switchm(6)=1;

     if response3=2 and Cd=1
       then switchd(4)=1;
     if response3=2 and Cd=2
       then switchd(5)=1;
     if response3=3 and Cd=1
       then switchd(6)=1;
end;

if group = 3 then
do;
```

```
        if response1=3 and Cf=3
           then switchf(7)=1;
        if response2=3 and Cm=3
           then switchm(7)=1;
        if response3=3 and Cd=3
           then switchd(7)=1;
    end;
run;

proc sql;
    create table DS3m.step3data2 as
    select /*1-7*/date, slot,
tvbcode,allslot1,cntslot1,allday1,cntday1,

/*8-12*/atvcode,allslot2,cntslot2,allday2,cntday2,
                          /*13-20*/SB1, SB2, SE1, SE2, B1, B2, E1,
E2,tvbslot, atvslot,
                          /*23-25*/fptvb, fpatv, fnowatch,
                          /*26-28*/mptvb, mpatv, mnowatch,
                          /*29-31*/dptvb, dpatv, dnowatch,
                          /*32-34*/choicef1,choicef2,choicef3,
                          /*35-37*/choicem1,choicem2,choicem3,
                          /*38-40*/choiced1,choiced2,choiced3,
                          /*41-43*/g1,g2,g3,

    /*44-49*/Sftvb1,Sftvb2,Sftvb3,Sfatv1,Sfatv2,Sfatv3,

    /*50-55*/Smtvb1,Smtvb2,Smtvb3,Smatv1,Smatv2,Smatv3,

    /*56-61*/Sdtvb1,Sdtvb2,Sdtvb3,Sdatv1,Sdatv2,Sdatv3,
                            /*62-63*/DTVB,DATV,

/*64-70*/switchf1,switchf2,switchf3,switchf4,switchf5,switchf6,switch
f7,

/*71-77*/switchm1,switchm2,switchm3,switchm4,switchm5,switchm6,switch
m7,

/*78-84*/switchd1,switchd2,switchd3,switchd4,switchd5,switchd6,switch
d7,
                          /*85-86*/conflict,flag
    from DS3m.step3data1;
quit;


proc iml;
    use DS3m.step3data2;
    read all into data;
    use DS3m.imlstep2_2;
    read all into input;

    Start maxFunc3(F) global(data,input);
        *NUM = 35;
        NUM = nrow(data);
        tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
        atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
        Vh=J(1,2,0);
        prob=0;
        sum = 0;

        do i = 1 to (NUM/7);
```

```
            prob=0;
                z = (i-1)*7+1;
                tvbcode = data[z,3];
                tvbtype = tvb_type[tvbcode];
                atvcode = data[z,8];
                atvtype = atv_type[atvcode];

                Uf1 = data[z,74]*F[77*0+tvbtype] +
(1-data[z,74])*(F[77*0+14+tvbtype] +
F[77*0+28+(tvbtype-1)*3+1]*data[z,44] +
F[77*0+28+(tvbtype-1)*3+2]*data[z,45] +
F[77*0+28+(tvbtype-1)*3+3]*data[z,46])
                         +
F[77*0+71]*data[z,17]+F[77*0+72]*data[z,18]+F[77*0+73]*data[z,19]+F[7
7*0+74]*data[z,20]+F[77*0+75]*data[z,13]+F[77*0+76]*data[z,15];
                Uf2 = data[z,75]*F[77*0+7+atvtype] +
(1-data[z,75])*(F[77*0+21+atvtype] +
F[77*0+49+(atvtype-1)*3+1]*data[z,47] +
F[77*0+49+(atvtype-1)*3+2]*data[z,48] +
F[77*0+49+(atvtype-1)*3+3]*data[z,49])
                         +
F[77*0+71]*data[z,17]+F[77*0+72]*data[z,18]+F[77*0+73]*data[z,19]+F[7
7*0+74]*data[z,20]+F[77*0+75]*data[z,14]+F[77*0+76]*data[z,16];

                Um1 = data[z,74]*F[77*1+tvbtype] +
(1-data[z,74])*(F[77*1+14+tvbtype] +
F[77*1+28+(tvbtype-1)*3+1]*data[z,50] +
F[77*1+28+(tvbtype-1)*3+2]*data[z,51] +
F[77*1+28+(tvbtype-1)*3+3]*data[z,52])
                         +
F[77*1+71]*data[z,17]+F[77*1+72]*data[z,18]+F[77*1+73]*data[z,19]+F[7
7*1+74]*data[z,20]+F[77*1+75]*data[z,13]+F[77*1+76]*data[z,15];
                Um2 = data[z,75]*F[77*1+7+atvtype] +
(1-data[z,75])*(F[77*1+21+atvtype] +
F[77*1+49+(atvtype-1)*3+1]*data[z,53] +
F[77*1+49+(atvtype-1)*3+2]*data[z,54] +
F[77*1+49+(atvtype-1)*3+3]*data[z,55])
                         +
F[77*1+71]*data[z,17]+F[77*1+72]*data[z,18]+F[77*1+73]*data[z,19]+F[7
7*1+74]*data[z,20]+F[77*1+75]*data[z,14]+F[77*1+76]*data[z,16];


                Ud1 = data[z,74]*F[77*2+tvbtype] +
(1-data[z,74])*(F[77*2+14+tvbtype] +
F[77*2+28+(tvbtype-1)*3+1]*data[z,56] +
F[77*2+28+(tvbtype-1)*3+2]*data[z,57] +
F[77*2+28+(tvbtype-1)*3+3]*data[z,58])
                         +
F[77*2+71]*data[z,17]+F[77*2+72]*data[z,18]+F[77*2+73]*data[z,19]+F[7
7*2+74]*data[z,20]+F[77*2+75]*data[z,13]+F[77*2+76]*data[z,15];
                Ud2 = data[z,75]*F[77*2+7+atvtype] +
(1-data[z,75])*(F[77*2+21+atvtype] +
F[77*2+49+(atvtype-1)*3+1]*data[z,59] +
F[77*2+49+(atvtype-1)*3+2]*data[z,60] +
F[77*2+49+(atvtype-1)*3+3]*data[z,61])
                         +
F[77*2+71]*data[z,17]+F[77*2+72]*data[z,18]+F[77*2+73]*data[z,19]+F[7
7*2+74]*data[z,20]+F[77*2+75]*data[z,14]+F[77*2+76]*data[z,16];

                Pf1 = exp(Uf1)/(exp(Uf1)+exp(Uf2)+exp(F[1*77]));
                Pf2 = exp(Uf2)/(exp(Uf1)+exp(Uf2)+exp(F[1*77]));
```

```
                Pf3 = exp(F[1*77])/(exp(Uf1)+exp(Uf2)+exp(F[1*77]));
                Pm1 = exp(Um1)/(exp(Um1)+exp(Um2)+exp(F[2*77]));
                Pm2 = exp(Um2)/(exp(Um1)+exp(Um2)+exp(F[2*77]));
                Pm3 = exp(F[2*77])/(exp(Um1)+exp(Um2)+exp(F[2*77]));
                Pd1 = exp(Ud1)/(exp(Ud1)+exp(Ud2)+exp(F[3*77]));
                Pd2 = exp(Ud2)/(exp(Ud1)+exp(Ud2)+exp(F[3*77]));
                Pd3 = exp(F[3*77])/(exp(Ud1)+exp(Ud2)+exp(F[3*77]));
            do j = 1 to 7;
                z = (i-1)*7+j;
                /* step1*/
                Prof=Pf1*data[z,32]+Pf2*data[z,33]+Pf3*data[z,34];
                Prom=Pm1*data[z,35]+Pm2*data[z,36]+Pm3*data[z,37];
                Prod=Pd1*data[z,38]+Pd2*data[z,39]+Pd3*data[z,40];

    ***************************************************************;
                /* step2 */
                /* interaction: fm fd fs md ms ds */

    Vh[1]=F[232]*data[z,32]+F[233]*data[z,35]+F[234]*data[z,38]+F[235
]*data[z,32]*data[z,35]+F[236]*data[z,32]*data[z,38]+F[237]*data[z,35
]*data[z,38];

    Vh[2]=F[232]*data[z,33]+F[233]*data[z,36]+F[234]*data[z,39]+F[235
]*data[z,33]*data[z,36]+F[236]*data[z,33]*data[z,39]+F[237]*data[z,36
]*data[z,39];
                duta1 = exp(Vh[1])/(exp(Vh[1])+exp(Vh[2])) ;
                duta2 = exp(Vh[2])/(exp(Vh[1])+exp(Vh[2])) ;
                duta3 = 1;
                group1 = (duta1*data[z,41] + duta2*data[z,42] +
duta3*data[z,43]) ** data[z,85];


    ***************************************************************;
                /* step3 */
                fP11=1;
                fP21=exp(Uf1)/(exp(Uf1)+exp(F[1*77]));
                fP23=exp(F[1*77])/(exp(Uf1)+exp(F[1*77]));
                fP12=exp(Uf2)/(exp(Uf2)+exp(F[1*77]));
                fP22=1;
                fP13=exp(F[1*77])/(exp(Uf2)+exp(F[1*77]));
                fP33=1;

                mP11=1;
                mP21=exp(Um1)/(exp(Um1)+exp(F[2*77]));
                mP23=exp(F[2*77])/(exp(Um1)+exp(F[2*77]));
                mP12=exp(Um2)/(exp(Um2)+exp(F[2*77]));
                mP22=1;
                mP13=exp(F[2*77])/(exp(Um2)+exp(F[2*77]));
                mP33=1;

                dP11=1;
                dP21=exp(Ud1)/(exp(Ud1)+exp(F[3*77]));
                dP23=exp(F[3*77])/(exp(Ud1)+exp(F[3*77]));
                dP12=exp(Ud2)/(exp(Ud2)+exp(F[3*77]));
                dP22=1;
                dP13=exp(F[3*77])/(exp(Ud2)+exp(F[3*77]));
                dP33=1;


    fP=fP11*data[z,64]+fP21*data[z,65]+fP23*data[z,66]+fP12*data[z,67
]+fP22*data[z,68]+fP13*data[z,69]+fP33*data[z,70];
```

```
    mP=mP11*data[z,71]+mP21*data[z,72]+mP23*data[z,73]+mP12*data[z,74
]+mP22*data[z,75]+mP13*data[z,76]+mP33*data[z,77];

    dP=dP11*data[z,78]+dP21*data[z,79]+dP23*data[z,80]+dP12*data[z,81
]+dP22*data[z,82]+dP13*data[z,83]+dP33*data[z,84];
                prob = prob + (Prof*Prom*Prod)*group1*(fP*mP*dP);
            end;/* End of j */
            sum = sum + log(prob) ;
        end;/* End of i */
        return (sum);
    Finish maxFunc3;
    optn={1 2};
    X = J(1,237,0);
    X[1:237] = input[1:237];

    con = J(2,239,.);
    con[1,1:237] = 0;
    con[2,1:237] = 1;
    do i = 1 to 14;
        con[1,77*0+i] = -5;
        con[1,77*1+i] = -5;
        con[1,77*2+i] = -5;
        con[2,77*0+i] = +5;
        con[2,77*1+i] = +5;
        con[2,77*2+i] = +5;
    end;

    con[1,232:237] = -5;
    con[2,232:237] = +5;

    tc = repeat(.,12);
    tc[1] = 4;
    tc[2] = 10;

    call nlpcg(rc,xres,"maxFunc3",X,optn,con,tc);
    Create DS3m.imlstep3 from xres ;
    Append from xres ;
quit;


/*********************************************************************
***********************/
/* Evaluation */

data DS3m.step3eva0;
    set DS3m.step2eva0;
run;

proc iml;
    use DS3m.imlstep3;
    read all into par1;

    use DS3m.step3eva0;
    read all into data;

    par = J(4,77,0);
    par[1,1:77] = par1[1,1:77];
    par[2,1:77] = par1[1,78:154];
    par[3,1:77] = par1[1,155:231];
    /*
```

```
        u:1-7:tvb, 8-14:atv
        duta:15-21, 22-28
        alpha:29-49:tvb, 50-70:atv
        beta:71-74
        gamma:75-76
        k1:77
    */
    tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
    atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
/*
         1-2:date slot
         3-7:tvbcode allslot1 cntslot1 allday1 cntday1
         8-12:atvcode allslot2 cntslot2 allday2 cntday2
         13-22:SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
         23-26:response1 response2 response3  group
         27-30:eresponse1 eresponse2 eresponse3 egroup
         31-39:ep1tvbu ep1atvu ek1 ep2tvbu ep2atvu ek2 ep3tvbu ep3atvu
ek3
         40-51:ef1-3, em1-3, ed1-3,eg1-3,
         52-57:w1-w6
*/
    do i = 1 to nrow(data);
        data[i,33] = par[1,77];
        data[i,36] = par[2,77];
        data[i,39] = par[3,77];
        data[i,52:57] = par1[1,232:237];
    end;
    do i = 1 to nrow(data);
        if data[i,7]  < 4 then
        do;
            tvbcode = data[i,3];
            tvbtype = tvb_type[tvbcode];
            data[i,31] = par[1,tvbtype] + par[1,71]*data[i,17] +
par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
par[1,75]*data[i,13] + par[1,76]*data[i,15];
            data[i,34] = par[2,tvbtype] + par[2,71]*data[i,17] +
par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
par[2,75]*data[i,13] + par[2,76]*data[i,15];
            data[i,37] = par[3,tvbtype] + par[3,71]*data[i,17] +
par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
par[3,75]*data[i,13] + par[3,76]*data[i,15];
        end;
        if data[i,12] < 4 then
        do;
            atvcode = data[i,8];
            atvtype = atv_type[atvcode];
            data[i,32] = par[1,7+atvtype] + par[1,71]*data[i,17] +
par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
par[1,75]*data[i,14] + par[1,76]*data[i,16];
            data[i,35] = par[2,7+atvtype] + par[2,71]*data[i,17] +
par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
par[2,75]*data[i,14] + par[2,76]*data[i,16];
            data[i,38] = par[3,7+atvtype] + par[3,71]*data[i,17] +
par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
par[3,75]*data[i,14] + par[3,76]*data[i,16];
        end;
    end;

    create DS3m.step3eval var{
        date slot
        tvbcode allslot1 cntslot1 allday1 cntday1
```

```
        atvcode allslot2 cntslot2 allday2 cntday2
        SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
        response1 response2 response3 group
        eresponse1 eresponse2 eresponse3 egroup
        ep1tvbu ep1atvu ek1 ep2tvbu ep2atvu ek2 ep3tvbu ep3atvu ek3
        ef1 ef2 ef3 em1 em2 em3 ed1 ed2 ed3 eg1 eg2 eg3
        w1 w2 w3 w4 w5 w6
        };
    append from data;
quit;

data DS3m.step3eva2;
    set DS3m.step3eva1;
    if cntday1 < 4 & cntday2 < 4 then
    do;
        if ep1tvbu > ep1atvu & 2*ep1tvbu + ep1atvu > 1 then do;ef1 =
1;ef3=0;end;
        if ep1atvu > ep1tvbu & 2*ep1atvu + ep1tvbu > 1 then do;ef2 =
1;ef3=0;end;
        if ep2tvbu > ep2atvu & 2*ep2tvbu + ep2atvu > 1 then do;em1 =
1;em3=0;end;
        if ep2atvu > ep2tvbu & 2*ep2atvu + ep2tvbu > 1 then do;em2 =
1;em3=0;end;
        if ep3tvbu > ep3atvu & 2*ep3tvbu + ep3atvu > 1 then do;ed1 =
1;ed3=0;end;
        if ep3atvu > ep3tvbu & 2*ep3atvu + ep3tvbu > 1 then do;ed2 =
1;ed3=0;end;
    end;
run;

proc iml;
    use DS3m.step3eva2;
    read all into data;

    use DS3m.imlstep3;
    read all into par1;

    par = J(4,77,0);
    par[1,1:77] = par1[1,1:77];
    par[2,1:77] = par1[1,78:154];
    par[3,1:77] = par1[1,155:231];

    Sf = J(1,3,0);
    Sm = J(1,3,0);
    Sd = J(1,3,0);
    tvb_type = {7,6,1,7,7,6,2,1,4,5,2,5,1,6,3,6,6,4,6,7,1,2};
    atv_type = {2,5,6,3,7,2,7,1,7,5,5,3,3,4,2,4,4,2,2,6,5,4,3,2};
/*
        1-2:date slot
        3-7:tvbcode allslot1 cntslot1 allday1 cntday1
        8-12:atvcode allslot2 cntslot2 allday2 cntday2
        13-22:SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
        23-26:response1 response2 response3  group
        27-30:eresponse1 eresponse2 eresponse3 egroup
        31-39:ep1tvbu ep1atvu ek1 ep2tvbu ep2atvu ek2 ep3tvbu ep3atvu
ek3
        40-51:ef1-3, em1-3, ed1-3,eg1-3,
        52-57:w1-w6
*/

    do i = 1 to nrow(data);
```

```
        if data[i,7] >= 4 then
        do;
            tvbcode = data[i,3];
            tvbtype = tvb_type[tvbcode];
            counter = 0;
            date = data[i,1];
            Sf[1:3] = 0;Sm[1:3] = 0;Sd[1:3] = 0;
                do j = 1 to 100;
                    k  = i - j;
                    if k < 1 then goto position1;
                    if data[k,3] = tvbcode then
                        if data[k,1] < data[i,1] then
                            do;
                                if data[k,1] < date then
                                    do;
                                        counter = counter + 1;
                                        date = data[k,1];
                                    end;
                                if counter = 4 then goto position1;
                                Sf[counter] =
Sf[counter]+data[i,40]/data[i,21];
                                Sm[counter] =
Sm[counter]+data[i,43]/data[i,21];
                                Sd[counter] =
Sd[counter]+data[i,46]/data[i,21];
                            end;
                end;
                position1:
                data[i,31] = par[1,14+tvbtype] + par[1,71]*data[i,17] +
par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
par[1,75]*data[i,13] + par[1,76]*data[i,15];
                data[i,34] = par[2,14+tvbtype] + par[2,71]*data[i,17] +
par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
par[2,75]*data[i,13] + par[2,76]*data[i,15];
                data[i,37] = par[3,14+tvbtype] + par[3,71]*data[i,17] +
par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
par[3,75]*data[i,13] + par[3,76]*data[i,15];
                data[i,31] = data[i,31] +
Sf[1]*par[1,28+(tvbtype-1)*3+1] + Sf[2]*par[1,28+(tvbtype-1)*3+2]  +
Sf[3]*par[1,28+(tvbtype-1)*3+3] ;
                data[i,34] = data[i,34] +
Sm[1]*par[2,28+(tvbtype-1)*3+1] + Sm[2]*par[2,28+(tvbtype-1)*3+2]  +
Sm[3]*par[2,28+(tvbtype-1)*3+3] ;
                data[i,37] = data[i,37] +
Sd[1]*par[3,28+(tvbtype-1)*3+1] + Sd[2]*par[3,28+(tvbtype-1)*3+2]  +
Sd[3]*par[3,28+(tvbtype-1)*3+3] ;
        end;
        if data[i,12] >= 4 then
        do;
            atvcode = data[i,8];
            atvtype = atv_type[atvcode];
            counter = 0;
            date = data[i,1];
            Sf[1:3] = 0;Sm[1:3] = 0;Sd[1:3] = 0;
                do j = 1 to 100;
                    k  = i - j;
                    if k < 1 then goto position2;
                    if data[k,8] = atvcode then
                        if data[k,1] < data[i,1] then
                            do;
                                if data[k,1] < date then
```

```
                                        do;
                                            counter = counter + 1;
                                            date = data[k,1];
                                        end;
                                    if counter = 4 then goto position2;
                                    Sf[counter] =
Sf[counter]+data[i,41]/data[i,22];
                                    Sm[counter] =
Sm[counter]+data[i,44]/data[i,22];
                                    Sd[counter] =
Sd[counter]+data[i,47]/data[i,22];
                                end;
                end;
                position2:
                atvcode = data[i,8];
                atvtype = atv_type[atvcode];
                data[i,32] = par[1,21+atvcode] + par[1,71]*data[i,17] +
par[1,72]*data[i,18] + par[1,73]*data[i,19] + par[1,74]*data[i,20] +
par[1,75]*data[i,14] + par[1,76]*data[i,16];
                data[i,35] = par[2,21+atvcode] + par[2,71]*data[i,17] +
par[2,72]*data[i,18] + par[2,73]*data[i,19] + par[2,74]*data[i,20] +
par[2,75]*data[i,14] + par[2,76]*data[i,16];
                data[i,38] = par[3,21+atvcode] + par[3,71]*data[i,17] +
par[3,72]*data[i,18] + par[3,73]*data[i,19] + par[3,74]*data[i,20] +
par[3,75]*data[i,14] + par[3,76]*data[i,16];
                data[i,32] = data[i,32] +
Sf[1]*par[1,49+(atvtype-1)*3+1] + Sf[2]*par[1,49+(atvtype-1)*3+2] +
Sf[3]*par[1,49+(atvtype-1)*3+3];
                data[i,35] = data[i,35] +
Sm[1]*par[2,49+(atvtype-1)*3+1] + Sm[2]*par[2,49+(atvtype-1)*3+2] +
Sm[3]*par[2,49+(atvtype-1)*3+3];
                data[i,38] = data[i,38] +
Sd[1]*par[3,49+(atvtype-1)*3+1] + Sd[2]*par[3,49+(atvtype-1)*3+2] +
Sd[3]*par[3,49+(atvtype-1)*3+3];
        end;

        if data[i,12] >= 4 | data[i,7] >= 4 then
        do;
            if data[i,31] > data[i,32] & 2*data[i,31] + data[i,32] > 1
then do;data[i,40] = 1; data[i,42]=0;end;
            if data[i,32] > data[i,31] & 2*data[i,32] + data[i,31] > 1
then do;data[i,41] = 1; data[i,42]=0;end;
            if data[i,34] > data[i,35] & 2*data[i,34] + data[i,35] > 1
then do;data[i,43] = 1; data[i,45]=0;end;
            if data[i,35] > data[i,34] & 2*data[i,35] + data[i,34] > 1
then do;data[i,44] = 1; data[i,45]=0;end;
            if data[i,37] > data[i,38] & 2*data[i,37] + data[i,38] > 1
then do;data[i,46] = 1; data[i,48]=0;end;
            if data[i,38] > data[i,37] & 2*data[i,38] + data[i,37] > 1
then do;data[i,47] = 1; data[i,48]=0;end;
        end;
    end;
    create DS3m.step3eva3 var{
        date slot
        tvbcode allslot1 cntslot1 allday1 cntday1
        atvcode allslot2 cntslot2 allday2 cntday2
        SB1 SB2 SE1 SE2 B1 B2 E1 E2 tvbslot atvslot
        response1 response2 response3 group
        eresponse1 eresponse2 eresponse3 egroup
        ep1tvbu ep1atvu k1 ep2tvbu ep2atvu k2 ep3tvbu ep3atvu k3
        ef1 ef2 ef3 em1 em2 em3 ed1 ed2 ed3 eg1 eg2 eg3
```

```
        w1 w2 w3 w4 w5 w6
        };
    append from data;
quit;

data DS3m.step3eva4;
    set DS3m.step3eva3;
    if ef1 = 1 then ef = 1;
    if ef2 = 1 then ef = 2;
    if ef3 = 1 then ef = 3;
    if em1 = 1 then em = 1;
    if em2 = 1 then em = 2;
    if em3 = 1 then em = 3;
    if ed1 = 1 then ed = 1;
    if ed2 = 1 then ed = 2;
    if ed3 = 1 then ed = 3;
run;


data DS3m.step3eva5;
    set DS3m.step3eva4;
    p1v1 = 0;
    p1v2 = 0;
    if ef = 1 then p1v1 = 1;
    if ef = 2 then p1v2 = 1;
    p2v1 = 0;
    p2v2 = 0;
    if em = 1 then p2v1 = 1;
    if em = 2 then p2v2 = 1;
    p3v1 = 0;
    p3v2 = 0;
    if ed = 1 then p3v1 = 1;
    if ed = 2 then p3v2 = 1;

   vote1 = w1*p1v1 + w2*p2v1 + w3*p3v1 + w4*p1v1*p2v1 + w5*p1v1*p3v1  +
w6*p2v1*p3v1;
   vote2 = w1*p1v2 + w2*p2v2 + w3*p3v2 + w4*p1v2*p2v2 + w5*p1v2*p3v2  +
w6*p2v2*p3v2;
***************************************************************;
   if vote1 = 0 and vote2 = 0 then
   do;
        egroup = 3;
        eresponse1 = 3;
        eresponse2 = 3;
        eresponse3 = 3;
   end;
   if vote1 = 0 and vote2 ^= 0 then egroup = 2;
   if vote1 ^= 0 and vote2 = 0 then egroup = 1;
   if vote1 ^= 0 and vote2 ^= 0 then
   do;
        egroup1 = exp(vote1) / ( exp(vote1) + exp(vote2) );
        ran = ranuni(117);
        if ran < egroup1 then egroup = 1;
        else egroup = 2 ;
   end;
***************************************************************;
   if vote1 = 0 and vote2 = 0 then
   do;
        bgroup = 3;
        bresponse1 = 3;
        bresponse2 = 3;
```

```
      bresponse3 = 3;
end;
if vote1 = 0 and vote2 ^= 0 then bgroup = 2;
if vote1 ^= 0 and vote2 = 0 then bgroup = 1;
if vote1 ^= 0 and vote2 ^= 0 then
do;
      bgroup1 = exp(vote1) / ( exp(vote1) + exp(vote2) ) ;
      if bgroup1>0.5 then bgroup = 1;
      else bgroup = 2 ;
end;

*************************************************************************;
if ( egroup = 1 ) and ( ef = 1) then eresponse1 = 1 ;
if ( egroup = 1 ) and ( em = 1) then eresponse2 = 1 ;
if ( egroup = 1 ) and ( ed = 1) then eresponse3 = 1 ;

if ( egroup = 1 ) and ( ef = 3) then eresponse1 = 3 ;
if ( egroup = 1 ) and ( em = 3) then eresponse2 = 3 ;
if ( egroup = 1 ) and ( ed = 3) then eresponse3 = 3 ;

if ( egroup = 2 ) and ( ef = 2) then eresponse1 = 2 ;
if ( egroup = 2 ) and ( em = 2) then eresponse2 = 2 ;
if ( egroup = 2 ) and ( ed = 2) then eresponse3 = 2 ;

if ( egroup = 2 ) and ( ef = 3) then eresponse1 = 3 ;
if ( egroup = 2 ) and ( em = 3) then eresponse2 = 3 ;
if ( egroup = 2 ) and ( ed = 3) then eresponse3 = 3 ;

  if (egroup = 1) and (ef = 2 ) then
   do  ;
       switch = exp(ep1tvbu) / ( exp(ep1tvbu)  + exp(k1) );
       ran = ranuni(118) ;
      if ran < switch then eresponse1 = 1 ;
        else eresponse1 = 3 ;
   end ;

  if (egroup = 1) and (em = 2 ) then
   do  ;
       switch = exp(ep2tvbu) / ( exp(ep2tvbu)  + exp(k2) );
       ran = ranuni(119) ;
      if ran < switch then eresponse2 = 1 ;
        else eresponse2 = 3 ;
   end ;

   if (egroup = 1) and (ed = 2 ) then
   do  ;
       switch = exp(ep3tvbu) / ( exp(ep3tvbu)  + exp(k3) );
       ran = ranuni(120) ;
      if ran < switch then eresponse3 = 1 ;
        else eresponse3 = 3 ;
   end ;

  if (egroup = 2) and (ef = 1 ) then
   do  ;
       switch = exp(ep1atvu) / ( exp(ep1atvu)  + exp(k1) );
       ran = ranuni(122) ;
      if ran < switch then eresponse1 = 2 ;
        else eresponse1 = 3 ;
   end ;

  if (egroup = 2) and (em = 1 ) then
```

```
do ;
    switch = exp(ep2atvu) / ( exp(ep2atvu)  + exp(k2) );
    ran = ranuni(123) ;
   if ran < switch then eresponse2 = 2 ;
    else eresponse2 = 3 ;
end ;

if (egroup = 2 ) and (ed = 1 ) then
do ;
    switch = exp(ep3atvu) / ( exp(ep3atvu)  + exp(k3) );
    ran = ranuni(124) ;
   if ran < switch then eresponse3 = 2 ;
    else eresponse3 = 3 ;
end ;
*****************************************************************;
if ( bgroup = 1 ) and ( ef = 1) then bresponse1 = 1 ;
if ( bgroup = 1 ) and ( em = 1) then bresponse2 = 1 ;
if ( bgroup = 1 ) and ( ed = 1) then bresponse3 = 1 ;

if ( bgroup = 1 ) and ( ef = 3) then bresponse1 = 3 ;
if ( bgroup = 1 ) and ( em = 3) then bresponse2 = 3 ;
if ( bgroup = 1 ) and ( ed = 3) then bresponse3 = 3 ;

if ( bgroup = 2 ) and ( ef = 2) then bresponse1 = 2 ;
if ( bgroup = 2 ) and ( em = 2) then bresponse2 = 2 ;
if ( bgroup = 2 ) and ( ed = 2) then bresponse3 = 2 ;

if ( bgroup = 2 ) and ( ef = 3) then bresponse1 = 3 ;
if ( bgroup = 2 ) and ( em = 3) then bresponse2 = 3 ;
if ( bgroup = 2 ) and ( ed = 3) then bresponse3 = 3 ;

if (bgroup = 1) and (ef = 2 ) then
  do ;
    bswitch = exp(ep1tvbu) / ( exp(ep1tvbu)  + exp(k1) )  ;
    if bswitch>0.5 then bresponse1 = 1 ;
     else bresponse1 = 3 ;
  end ;

 if (bgroup = 1) and (em = 2 ) then
  do ;
     bswitch = exp(ep2tvbu) / ( exp(ep2tvbu)  + exp(k2) )  ;
    if bswitch>0.5 then bresponse2 = 1 ;
     else bresponse2 = 3 ;
  end ;

 if (bgroup = 1) and (ed = 2 ) then
  do ;
     bswitch = exp(ep3tvbu) / ( exp(ep3tvbu)  + exp(k3) )  ;
    if bswitch>0.5 then bresponse3 = 1 ;
     else bresponse3 = 3 ;
  end ;

 if (bgroup = 2) and (ef = 1 ) then
  do ;
     bswitch = exp(ep1atvu) / ( exp(ep1atvu)  + exp(k1) )  ;
    if bswitch>0.5 then bresponse1 = 2 ;
     else bresponse1 = 3 ;
   end ;

 if (bgroup = 2) and (em = 1 ) then
  do ;
```

```
        bswitch = exp(ep2atvu) / ( exp(ep2atvu)  + exp(k2) )  ;
       if bswitch>0.5 then bresponse2 = 2 ;
        else bresponse2 = 3 ;
     end ;

   if (bgroup = 2 ) and (ed = 1 ) then
     do  ;
        bswitch = exp(ep3atvu) / ( exp(ep3atvu)  + exp(k3) )  ;
       if bswitch>0.5 then bresponse3 = 2 ;
        else bresponse3 = 3 ;
     end ;

run;
****************************************************************;

data DS3m.h3(keep=date slot group egroup response1 response2 response3
eresponse1 eresponse2 eresponse3 bresponse1 bresponse2 bresponse3 );
    set DS3m.step3eva5;
run;
****************************************************************;
proc freq data = DS3m.h3;
   tables group * egroup / chisq;

    tables response1 * eresponse1 / chisq;
    tables response2 * eresponse2 / chisq;
    tables response3 * eresponse3 / chisq;

    tables response1 * bresponse1 / chisq;
    tables response2 * bresponse2 / chisq;
    tables response3 * bresponse3 / chisq;
run;
```

APPENDIX 4 SAMPLE SIMULATION PROGRAM

```
****************************************************************;
do j = 1 to 1000 ;
  time = j ;
  if time<401 then
    do;
        showtvb = int(2*ranuni(106) ) + 1 ;
         showatv = int(2*ranuni(107))  + 1 ;
    end;
  if time>400 then
    do;
         showtvb = int(3*ranuni(106) ) + 3 ;
         showatv = int(3*ranuni(107))  + 3 ;
    end;

  ****************************************************************;
  u1tvb =   p1tvb(showtvb)  ;
  u1atv =   p1atv(showatv)  ;

  prob1tvb = exp(u1tvb) /  ( exp(u1tvb) + exp(u1atv) + exp(k1) ) ;
  prob1atv = exp(u1atv) /  ( exp(u1tvb) + exp(u1atv) + exp(k1) ) ;

  ran = ranuni(110) ;
  choice1 = 3 ;
  if ran < prob1tvb then choice1 = 1 ;
  if ( ran > prob1tvb ) and ( ran < prob1tvb + prob1atv ) then
  choice1 = 2 ;

  /* Benchmark */
  bchoice1 = 3;
  if prob1tvb>prob1atv and 2*prob1tvb+prob1atv>1
  then bchoice1=1;
  if prob1atv>prob1tvb and 2*prob1atv+prob1tvb>1
  then bchoice1=2;

  ****************************************************************;
  u2tvb =   p2tvb(showtvb)  ;
  u2atv =   p2atv(showatv)  ;

  prob2tvb = exp(u2tvb) /  ( exp(u2tvb) + exp(u2atv) + exp(k2) ) ;
  prob2atv = exp(u2atv) /  ( exp(u2tvb) + exp(u2atv) + exp(k2) ) ;

  ran = ranuni(113) ;
  choice2 = 3 ;
  if ran < prob2tvb then choice2 = 1 ;
  if ( ran > prob2tvb ) and ( ran < prob2tvb + prob2atv ) then
  choice2 = 2 ;

   /* Benchmark */
  bchoice2 = 3;
  if prob2tvb>prob2atv and 2*prob2tvb+prob2atv>1
  then bchoice2=1;
  if prob2atv>prob2tvb and 2*prob2atv+prob2tvb>1
  then bchoice2=2;
 ****************************************************************;
  u3tvb =   p3tvb(showtvb) ;
```

```
u3atv =   p3atv(showatv)  ;

prob3tvb = exp(u3tvb) /  ( exp(u3tvb) + exp(u3atv) + exp(k3) ) ;
prob3atv = exp(u3atv) /  ( exp(u3tvb) + exp(u3atv) + exp(k3) ) ;

ran = ranuni(116) ;
choice3 = 3 ;
if ran < prob3tvb then choice3 = 1 ;
if ( ran > prob3tvb ) and ( ran < prob3tvb + prob3atv ) then
choice3 = 2 ;

/* Benchmark */
bchoice3 = 3;
if prob3tvb>prob3atv and 2*prob3tvb+prob3atv>1
then bchoice3=1;
if prob3atv>prob3tvb and 2*prob3atv+prob3tvb>1
then bchoice3=2;
**************************************************************;
p1v1 = 0 ;
p1v2 = 0 ;
if choice1 = 1 then p1v1 = 1 ;
if choice1 = 2 then p1v2 = 1 ;

 p2v1 = 0 ;
 p2v2 = 0 ;
 if choice2 = 1 then p2v1 = 1 ;
 if choice2 = 2 then p2v2 = 1 ;

 p3v1 = 0 ;
 p3v2 = 0 ;
 if choice3 = 1 then p3v1 = 1 ;
 if choice3 = 2 then p3v2 = 1 ;

 vote1 = w1*p1v1 + w2*p2v1 + w3*p3v1 + w12*p1v1*p2v1 + w13*p1v1*p3v1
+ w23*p2v1*p3v1;
 vote2 = w1*p1v2 + w2*p2v2 + w3*p3v2 + w12*p1v2*p2v2 + w13*p1v2*p3v2
+ w23*p2v2*p3v2;

 if vote1 = 0 and vote2 = 0 then
 do;
       group = 3;
       response1 = 3;
       response2 = 3;
       response3 = 3;
 end;
 if vote1 = 0 and vote2 ^= 0 then group = 2;
 if vote1 ^= 0 and vote2 = 0 then group = 1;
 if vote1 ^= 0 and vote2 ^= 0 then
 do;
       group1 = exp(vote1) / ( exp(vote1) + exp(vote2) ) ;
       ran = ranuni(117);
       if ran < group1 then group = 1;
       else group = 2 ;
 end;


**************************************************************;
bp1v1 = 0 ;
bp1v2 = 0 ;
if bchoice1 = 1 then bp1v1 = 1 ;
if bchoice1 = 2 then bp1v2 = 1 ;
```

```
   bp2v1 = 0 ;
   bp2v2 = 0 ;
   if bchoice2 = 1 then bp2v1 = 1 ;
   if bchoice2 = 2 then bp2v2 = 1 ;

   bp3v1 = 0 ;
   bp3v2 = 0 ;
   if bchoice3 = 1 then bp3v1 = 1 ;
   if bchoice3 = 2 then bp3v2 = 1 ;

   bvote1 = w1*bp1v1 + w2*bp2v1 + w3*bp3v1 + w12*bp1v1*bp2v1 +
w13*bp1v1*bp3v1 + w23*bp2v1*bp3v1;
   bvote2 = w1*bp1v2 + w2*bp2v2 + w3*bp3v2 + w12*bp1v2*bp2v2 +
w13*bp1v2*bp3v2 + w23*bp2v2*bp3v2;

   if bvote1 = 0 and bvote2 = 0 then
   do;
         bgroup = 3;
         bresponse1 = 3;
         bresponse2 = 3;
         bresponse3 = 3;
   end;
   if bvote1 = 0 and bvote2 ^= 0 then bgroup = 2;
   if bvote1 ^= 0 and bvote2 = 0 then bgroup = 1;
   if bvote1 ^= 0 and bvote2 ^= 0 then
   do;
         bgroup1 = exp(bvote1) / ( exp(bvote1) + exp(bvote2) ) ;
         if bgroup1>0.5 then bgroup = 1;
         else bgroup = 2 ;

   end;

   *****************************************************************;
   if ( group = 1 ) and ( choice1 = 1) then response1 = 1 ;
   if ( group = 1 ) and ( choice2 = 1) then response2 = 1 ;
   if ( group = 1 ) and ( choice3 = 1) then response3 = 1 ;

   if ( group = 1 ) and ( choice1 = 3) then response1 = 3 ;
   if ( group = 1 ) and ( choice2 = 3) then response2 = 3 ;
   if ( group = 1 ) and ( choice3 = 3) then response3 = 3 ;

   if ( group = 2 ) and ( choice1 = 2) then response1 = 2 ;
   if ( group = 2 ) and ( choice2 = 2) then response2 = 2 ;
   if ( group = 2 ) and ( choice3 = 2) then response3 = 2 ;

   if ( group = 2 ) and ( choice1 = 3) then response1 = 3 ;
   if ( group = 2 ) and ( choice2 = 3) then response2 = 3 ;
   if ( group = 2 ) and ( choice3 = 3) then response3 = 3 ;


   if (group = 1) and (choice1 = 2 ) then
      do ;
          switch = exp(ultvb) / ( exp(ultvb)  + exp(k1) )  ;
          ran = ranuni(118) ;
         if ran < switch then response1 = 1 ;
          else response1 = 3 ;
      end ;

     if (group = 1) and (choice2 = 2 ) then
      do ;
```

```
        switch = exp(u2tvb) / ( exp(u2tvb)  + exp(k2) )  ;
        ran = ranuni(119) ;
       if ran < switch then response2 = 1 ;
        else response2 = 3 ;
    end ;

    if (group = 1) and (choice3 = 2 ) then
    do  ;
        switch = exp(u3tvb) / ( exp(u3tvb)  + exp(k3) )  ;
        ran = ranuni(120) ;
       if ran < switch then response3 = 1 ;
        else response3 = 3 ;
    end ;

 if (group = 2) and (choice1 = 1 ) then
    do  ;
        switch = exp(u1atv) / ( exp(u1atv)  + exp(k1) )  ;
        ran = ranuni(121) ;
       if ran < switch then response1 = 2 ;
        else response1 = 3 ;
    end ;

   if (group = 2) and (choice2 = 1 ) then
    do  ;
        switch = exp(u2atv) / ( exp(u2atv)  + exp(k2) )  ;
        ran = ranuni(122) ;
       if ran < switch then response2 = 2 ;
        else response2 = 3 ;
    end ;

    if (group = 2 ) and (choice3 = 1 ) then
    do  ;
        switch = exp(u3atv) / ( exp(u3atv)  + exp(k3) )  ;
        ran = ranuni(123) ;
       if ran < switch then response3 = 2 ;
        else response3 = 3 ;
    end ;


**************************************************************;

  if ( bgroup = 1 ) and ( bchoice1 = 1) then bresponse1 = 1 ;
  if ( bgroup = 1 ) and ( bchoice2 = 1) then bresponse2 = 1 ;
  if ( bgroup = 1 ) and ( bchoice3 = 1) then bresponse3 = 1 ;

  if ( bgroup = 1 ) and ( bchoice1 = 3) then bresponse1 = 3 ;
  if ( bgroup = 1 ) and ( bchoice2 = 3) then bresponse2 = 3 ;
  if ( bgroup = 1 ) and ( bchoice3 = 3) then bresponse3 = 3 ;

  if ( bgroup = 2 ) and ( bchoice1 = 2) then bresponse1 = 2 ;
  if ( bgroup = 2 ) and ( bchoice2 = 2) then bresponse2 = 2 ;
  if ( bgroup = 2 ) and ( bchoice3 = 2) then bresponse3 = 2 ;

  if ( bgroup = 2 ) and ( bchoice1 = 3) then bresponse1 = 3 ;
  if ( bgroup = 2 ) and ( bchoice2 = 3) then bresponse2 = 3 ;
  if ( bgroup = 2 ) and ( bchoice3 = 3) then bresponse3 = 3 ;


  if (bgroup = 1) and (bchoice1 = 2 ) then
    do  ;
```

```
      bswitch = exp(u1tvb) / ( exp(u1tvb)  + exp(k1) )  ;
      if bswitch>0.5 then bresponse1 = 1 ;
       else bresponse1 = 3 ;
   end ;

   if (bgroup = 1) and (bchoice2 = 2 ) then
   do  ;
       bswitch = exp(u2tvb) / ( exp(u2tvb)  + exp(k2) )  ;
      if bswitch>0.5 then bresponse2 = 1 ;
       else bresponse2 = 3 ;
   end ;

   if (bgroup = 1) and (bchoice3 = 2 ) then
   do  ;
       bswitch = exp(u3tvb) / ( exp(u3tvb)  + exp(k3) )  ;
      if bswitch>0.5 then bresponse3 = 1 ;
       else bresponse3 = 3 ;
   end ;

 if (bgroup = 2) and (bchoice1 = 1 ) then
   do  ;
       bswitch = exp(u1atv) / ( exp(u1atv)  + exp(k1) )  ;
      if bswitch>0.5 then bresponse1 = 2 ;
       else bresponse1 = 3 ;
   end ;

   if (bgroup = 2) and (bchoice2 = 1 ) then
   do  ;
       bswitch = exp(u2atv) / ( exp(u2atv)  + exp(k2) )  ;
      if bswitch>0.5 then bresponse2 = 2 ;
       else bresponse2 = 3 ;
   end ;

   if (bgroup = 2 ) and (bchoice3 = 1 ) then
   do  ;
       bswitch = exp(u3atv) / ( exp(u3atv)  + exp(k3) )  ;
      if bswitch>0.5 then bresponse3 = 2 ;
       else bresponse3 = 3 ;
   end ;

   output ;

end ;

run;
***************************************************************************;
proc freq data = simulation;
    tables group * bgroup / chisq;

    tables response1 * bresponse1 / chisq;
    tables response2 * bresponse2 / chisq;
    tables response3 * bresponse3 / chisq;

run;
***************************************************************************;
quit;
```

APPENDIX 5 TIMESLOT DEFINITION

No.	Starting	Ending	Duration (min)
1	18:00	18:09	10
2	18:10	18:19	10
3	18:20	18:29	10
4	18:30	18:39	10
5	18:45	18:59	15
6	19:00	19:09	10
7	19:10	19:19	10
8	19:20	19:29	10
9	19:30	19:39	10
10	19:40	19:49	10
11	19:50	19:59	10
12	20:00	20:09	10
13	20:10	20:19	10
14	20:20	20:29	10
15	20:30	20:39	10
16	20:40	20:49	10
17	20:50	20:59	10
18	21:00	21:09	10
19	21:10	21:19	10
20	21:20	21:29	10
21	21:30	21:39	10
22	21:40	21:49	10
23	21:50	21:59	10
24	22:00	22:09	10
25	22:10	22:19	10
26	22:20	22:29	10
27	22:30	22:39	10
28	22:40	22:49	10
29	22:50	22:59	10
30	23:00	23:09	10
31	23:10	23:14	5
32	23:15	23:24	10
33	23:25	23:34	10
34	23:35	23:44	10
35	23:45	23:49	5
36	23:50	24:00	10