THE PRICE OF LOYALTY: A GENDERED ANALYSIS OF CONSUMER SURVEILLANCE

By

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A thesis submitted to the Graduate Program in Sociology
in conformity with the requirements for the
Degree of Master of Arts

Queen’s University
Kingston, Ontario, Canada
June, 2013

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Abstract

Consumer surveillance, seen in the social sorting capabilities of loyalty marketing, is gendered. Using Canadian examples, gender is added to the existing literature on social sorting in relation to class (Burrows and Gane 2006; Parker, Uprichard and Burrows 2007) and racial or ethnic background (Gandy 1993; 1996; 2006a; 2006b; 2010; 2011). The prevalence of loyalty programs in Canada raises some significant issues regarding social sorting, as they tend to allocate unequal life chances and choices based on certain aspects of individuals’ profiles, allowing retailers to focus their efforts and resources toward their most desirable clientele. It is important to consider the role that gender plays in loyalty marketing in order to understand how being labelled a ‘man’ or a ‘woman’ can influence how one’s personal information is categorized and utilized by companies. As these programs use data mining and social sorting techniques to attract preferred customers, men and women are targeted in different ways by different loyalty marketing schemes, depending on the perceived value of their digitized profiles. The findings of the 2006 Globalization of Personal Data survey are interrogated for a background analysis of gender and loyalty. A statistical analysis of the Canadian responses investigates whether membership rates and popular attitudes about loyalty programs vary significantly between different demographic groups.
Acknowledgements

Thank you to everyone who has influenced my research over the past two years. First and foremost I would like to thank my supervisor and mentor Dr. David Lyon for his unwavering support, enthusiasm and guidance throughout the entire process. I am fortunate to have had the opportunity to work with such an eminent scholar who is also extremely dedicated to scholarship, teaching, and his students. His genuine understanding and reassurance during times when I was feeling doubtful or discouraged about my work gave me the confidence to pursue my research and for that I am eternally grateful. I would like to thank Jones Adjei for the hours he spent in the computer lab teaching me how to compute my statistics using Stata, and his enduring patience while doing so. Though unfortunately he is no longer with us, thanks are also due to Dr. Stephen Obeng Gyimah for his advice and guidance during the preliminary stages of my statistical research. I do not have a strong background in statistics and his admirable enthusiasm for teaching made the statistical process of my research less daunting.

I would like to thank Dr. Elia Zureik for giving me the opportunity to develop my statistical skills while working with him as a research assistant. Thank you to Dr. Ken Wong for sharing his marketing expertise with me and providing advice on how to contact potential interviewees. Thank you to the other members of my thesis committee, Dr. Martin Hand and Dr. Jay Handelman. I would also like to thank members of the department of sociology, especially Michelle Ellis and Wendy Schuler, as well as Emily Smith, Joan Sharpe, and others in the Surveillance Studies Centre. Thank you to Dr. Rob Beamish, Dr. Martin Hand, and Dr. Richard Day for their guidance during my TAships. Thank you to William Lockrey for being so supportive throughout the writing process and thank you to my parents Dr. Patricia Cheston and Dr. Jim Cheston for their undying love and encouragement
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Chapter One

Introduction

Gender is inadequately addressed in surveillance studies. Although some scholars like Kirstie Ball (2002; 2004), Hille Koskela (2006; 2008; 2012) and Bailey and Steeves (2013, forthcoming) examine gender in such contexts as public space camera and workplace surveillance, the gendered dimensions of consumer surveillance in particular are relatively unexplored. This is surprising given the fact that women are usually considered to be predominant consumers. Consumerism in contemporary North America represents a *society of consumers* where the authenticity of one’s membership in society is confirmed by the individual’s acquired status as a sellable commodity (Bauman 2007). The commoditization of consumer information has been facilitated by sophisticated databases that can aggregate, update and sort information about individuals in a highly refined manner to help marketers develop personalized advertising schemes (CIPPIC 2006). The collection, sorting and profiling of consumer data has been brought to the forefront of popular marketing approaches, partly due to the recent proliferation of loyalty programs in North America. For small incentives like collecting ‘points’ and receiving discounts, members provide detailed information about themselves and their shopping behaviours, often without realizing how their information is being used and who can access it (Everett 2009).

The prevalence of loyalty programs in Canada raises significant issues regarding social sorting, as they can allocate unequal life chances and choices based on certain aspects of consumer profiles, allowing retailers to focus their efforts and resources toward their most desirable clientele. Although much has been written about the social sorting capabilities of database technology in relation to class (Sivadas, Mathew and Curry 1997; Burrows and Gane 2006; Parker, Uprichard and Burrows 2007) and racial or ethnic background (Gandy 1993; 1996;
the existing literature on social sorting and gender is rather limited. It is important to consider the role that gender plays in loyalty marketing in order to understand how being labelled a ‘man’ or a ‘woman’ can influence how one’s personal information is classified and utilized by companies. Using a variety of sociological perspectives on commercial surveillance and social sorting, along with business perspectives on loyalty marketing, this research will examine the gendered dimensions of consumer surveillance seen in loyalty programs in Canada.

Loyalty programs reward consumers for their repeated business at a certain store, chain, or combination of stores by offering enticements such as individual recognition, improved customer service, discounts, and special deals in exchange for consumer loyalty and information (Pridmore 2010a). These programs are becoming increasingly omnipresent in Western marketing initiatives; in Canada there are roughly 121 million loyalty program memberships among a population of 33.5 million, making the country one of the most highly penetrated, mature loyalty markets in the world (Pearson 2012c). Affinity programs serve as prototypes of contemporary corporate-consumer relationships in North America, as approximately 90 percent of Canada are members of at least one (Hlavinka and Sullivan 2011). The data collection strategies employed by loyalty programs raise some important surveillance-related issues because consumers are generally uninformed about how their information is being extracted and used, as well as who can access their profiles (Manzerolle and Smeltzer 2011).

I conceptualize loyalty marketing as a form of contemporary surveillance, defined as “purposeful, routine, systematic and focused attention paid to personal details, for the sake of control, entitlement, management, influence or protection,” (Murakami Wood and Ball 2006:3). More specifically, the data collection and categorization practices that are involved in loyalty
marketing will be contextualized as examples of *everyday surveillance* referring to “a focused attention to personal details aimed at exerting an influence over or managing the objects of the data, or ‘data subjects’ as they are sometimes called,” (Lyon 2002:242). Surveillance has become the “defining practice” of most organizations in the 21st century, as it is constantly employed to analyze and evaluate subjects in various ways (Pridmore and Lyon 2011:116). As Lyon concisely asserts, “Much everyday convenience, efficiency and security depends upon surveillance,” (2002:243). This is exemplified through the way that companies use loyalty marketing to develop interactive relationships with their customers that are established and maintained through the collection of personal information, allowing corporations to identify their most valuable clientele (Capizzi and Ferguson 2005). Every product bought by a specific consumer is tracked using customer identifiers, usually in the form of barcode or magstripe cards, which record purchasing behaviour (Pridmore 2010b). By combining records from consumer databases with other sources of personal information on the Internet, marketers can obtain a “360 degree view” of customers, facilitating automated profiling and sorting (Danna and Gandy 2002). Thus, loyalty marketing clearly embodies a form of contemporary surveillance.

In Canada, certain corporations have a much higher penetration of loyalty cards than others. Air Miles, the largest coalition loyalty program in Canada, has 70 percent of Canadian households as members and gathers information from over $80 billion of customer spending, making it one of the most successful programs in the world (Pearson 2012b). Instituted in Canada during 1992, this widely popular coalition program offers a range of redeemable rewards from flights, to Garmin GPS systems, to Samsung 46 inch LED TVs (Buckland 2011). Currently, only ten thousand of their ten million active households have opted out of the targeted marketing offered by the program, meaning that 99.99 percent of members consent to receiving
individualized communications (Pearson 2012b). Although it is not as prevalent as Air Miles, with only 29 percent of Canadians as members, Aeroplan claims to have 92 percent of business travelers in its reward program (Pridmore 2010b). Beginning in 1984 as a frequent flier add-on for Air Canada, and then uniting with the CIBC Aerogold Visa in 1991, Aeroplan has developed multiple branding schemes with over 150 brands to date, including Esso, Hilton, and Home Hardware (Buckland 2011).

In contrast with these airline-rooted programs, the Shoppers Optimum program is another prominent loyalty scheme in Canada, with approximately 50 percent of Canadian women as members (Pridmore 2010b). Shoppers Drug Mart has become a leading figure among Canadian loyalty programs since the introduction of the Optimum card in the late 1990s, which awards customers ten redeemable points for every dollar spent at the store (Buckland 2011). On rare occasions throughout the year, Optimum card holders have the opportunity to get twenty, or even fifty times the points for every dollar spent on products at Shoppers Drug Mart, which undoubtedly entices many consumers to shop and spend more during those times (ibid.). Though not as ubiquitous as Air Miles or Shoppers Optimum, several other loyalty programs are quickly gaining popularity among Canadian consumers; these include Club Sobeys, Petro-Points, HBC Rewards, and the Scotiabank SCENE card (ibid.).

Aside from successful enrolment rates, the major aim of loyalty marketing is to decrease attrition. A recent survey by Maritz Canada that investigated the influence of loyalty marketing on purchasing decisions and involved approximately 6500 consumers suggests that Canadian rewards programs are generally successful; of all the participants, 62 percent reported that loyalty programs have a positive impact on their likelihood to continue doing business with a specific company (Daniel and Davies 2012). Clearly, Canada represents a highly conducive
market for loyalty programs; accordingly it can be assumed that most Canadian consumers engage and participate in what seem to be mutually beneficial relationships with retailers through their membership in one or several of these programs.

Since many companies from various industries tend to share a similar consumer base, several firms have started forming multiple branding schemes and coalition programs that allow customers to gain points from shopping for certain brands at certain stores, while permitting the combination and transfer of benefits – Air Miles is the most prominent example of this (Pridmore 2010b). Furthermore, many financial institutions now offer rewards programs with their credit cards, and propriety and coalition cards can also be co-branded with a credit card (ibid.). Unlike other corporate promotional tools, these programs are long-term and focus on maintaining relationships with existing customers in order to amplify the rate that goods are consistently purchased from a certain company, brand or store (Lacey and Sneath 2006).

The underlying strategy of these programs is Customer Relationship Management (CRM) which focuses on share of consumer rather than share of market, and is based on the logic that a company can inflate profits by directing their marketing resources towards increasing the business of existing customers instead of increasing the amount of customers overall (Danna and Gandy 2002). This strategy rests on the marketing notion known as the Pareto Principle, which claims that eighty percent of any firm’s profit is acquired from twenty percent of its entire clientele; loyalty programs seek to develop closer relationships with this valuable twenty percent by using data mining techniques to illuminate their most profitable customers and make predictions about who should be targeted for future marketing initiatives (ibid.). In this way, the probability of receiving corporate offers changes from customer to customer, depending on how well one’s digital consumer profile complements the marketing objective of a particular
campaign (Pridmore and Lyon 2011). Thus, companies that employ CRM seek to attract the ‘best consumers’ by selectively developing and preserving lasting relationships with them; those who regularly disclose personal information and are regarded as ‘loyal’ shoppers are often deemed most desirable (Turow 2006b).

Loyalty marketing exemplifies how surveillance has become a commoditized feature of contemporary consumption and the social relations within them; in order to ‘count’ as a consumer subject, one must be transformed into a commodity through the construction of a database profile (Zurawski 2011). Upon joining a rewards program, individuals are asked to provide various types of demographic, geographic and psychographic data that are used to construct their initial consumer profiles (Rowley 2004). As members continue to participate in the program, information about consumer behaviour such as purchase frequency, brand loyalty, product preferences and receptiveness to advertising are recorded and stored in the company’s database; information provided by third parties, including census bureaus and data brokers, are also commonly used by retailers to develop “layers of data” (Pridmore 2010a:572) that portray a comprehensive portrait of a given consumer. In this respect, corporate-consumer relations can be understood in terms of branding, as customers are commonly reduced to a more simplified concept based on their location, demographic information, and purchasing behaviour (Lury 2005). Furthermore, the ability of corporations to know their customers on a more individual level through loyalty marketing resembles how branding can make products recognizable and known in certain ways (Pridmore and Lyon 2011). All of these aspects of loyalty marketing make it understandable as a form of commercial sociology; by using similar methods of data collection to the social sciences and analyzing digital consumer profiles in relation to aggregated
groups of consumers that have been categorized in similar ways, marketers can predict different courses and patterns of consumption (ibid.).

This research questions how gender is implicated in commercial surveillance and loyalty marketing in contemporary Canadian society, and how other demographic factors influence these practices. I investigate how far certain groups are significantly more or less inclined to participate in loyalty programs and have more or less favourable attitudes toward certain aspects of data collection in this context. To address these questions, findings from the 2006 Globalization of Personal Data survey will be interrogated for a background analysis of gender and loyalty. A statistical analysis of the Canadian responses will examine whether membership rates and popular attitudes about loyalty programs vary significantly between different demographic groups that are defined by gender, age, income, region, race/ethnicity, and education. Drawing on interviews that were conducted with two prominent loyalty marketing executives, business perspectives on loyalty and different demographic groups – with particular focus on gender, age, and income – will complement the statistical findings.
Chapter Two
From Stamps to Software: An Overview of Customer Loyalty

This chapter presents an overview of the existing literature on gender, loyalty marketing, and consumer surveillance. By combining research from different areas, this chapter summarizes what is known about gender and consumer surveillance so far, and acts as a springboard into my research. The following chapters will outline how the discrepancies in existing literature can be improved and where this research could go in the future, through an exploratory study of gender and consumer surveillance in loyalty programs.

Historical Background

The ideological foundation of loyalty programs can be historically traced back to 1896, when the Sperry and Hutchinson (S&H) company’s Green Stamps first emerged in the United States (Lacey and Sneath 2006). Customers would receive stamps from shopping at supermarkets, department stores, gas stations and other retailers, which could be traded in for products in their catalogue (Lach 2000). S&H Green Stamps remained popular in the United States from the 1930s to late 1980s (Lacey and Sneath 2006). This development took place at a time when market research was undergoing a general shift in focus to categorizing customers according to their various drives and priorities (Zwick and Dholakia 2004b). Following World War II, corporations began to focus their energies on compiling consumers into marketable categories using demographic and psychographic information; these early sorting practices became significantly refined with the introduction of large-scale consumer databases that were first employed in relation to consumer credit and geo-demographic information systems (Pridmore and Zwick 2011). The introduction of psychographics in the 1970s and geo-demographics in the 1980s facilitated the development of market segmentation, as they enabled
the direct targeting of specific audiences for different marketing campaigns; however the relatively slow, vague, and non-interactive nature of market feedback technology hindered any further advancement towards the highly-refined and efficient means of consumer identification that characterizes market research today (ibid.).

While market research had previously emphasized sales and transaction-oriented approaches, marketers began to endorse intimate, one-to-one relationships with consumers during the late 1980s as a means to achieving success in a competitive market. (Zwick and Dholakia 2004b). As stamp reward programs gradually declined in appeal during the 1980s, newer versions of loyalty cards became increasingly popular following the launch of American Airlines’ frequent flyer program in 1981 – the first modern loyalty scheme in North America (ibid.). Since then, the technological expansion of the 1990s and its extension into the 21st century have facilitated the growth of numerous loyalty programs throughout North America and other economically developed countries (Lacey and Sneath 2006). In particular, corporate marketing initiatives during the past twenty years have demonstrated a dramatically greater level of surveillance that is exercised over consumers and their consumption habits, due largely to the fact that such practices situate contemporary companies in an advantageous position within highly competitive capitalist markets (Pridmore and Zwick 2011). Moreover, contemporary consumer databases enable the mass collection, storage and retrieval of consumer data at a minor cost (Pridmore 2010b). Loyalty programs capitalize on this technology by using it in tandem with advanced analytic programs such as data mining and knowledge data discovery (KDD), which are employed under the principal marketing strategy of CRM in order to build detailed profiles of individual consumers (ibid.).
Defining Loyalty

Customer loyalty has traditionally been classified as a behavioural measure, meaning that loyalty corresponds to purchasing behaviour and is fuelled by rewards (Pearson 2012b). Measures of purchase behaviour that are used to determine behavioural loyalty include proportion of purchase, probability of purchase and repurchase, purchase frequency, and purchase sequence, among others (Kumar and Shah 2004). While behavioural loyalty is typically weak and temporary, attitudinal or emotional loyalty characterizes a long-term commitment of the customer to the brand or company that cannot be surmised by monitoring repeat purchase behaviour (ibid.). Attitudinal loyalty is comparable to brand loyalty, and reflects the ability of a company to directly identify the contributions of the consumer and build a meaningful one-to-one relationship with them; hence, a customer who displays this type of loyalty is more valuable to a business than one who merely exhibits behavioural loyalty (Pearson 2012b).

Loyalty marketers argue that they must know their customers well beyond their purchasing records in order to efficiently and successfully develop attitudinal loyalty, so consumer profiles containing demographic and psychographic information are utilized to predict future consumption patterns and profitability (Kumar and Shah 2004). Through the use of advanced data collection and analysis technology, businesses can acquire several relevant data points on a consumer and effectively enhance their attitudinal loyalty by fulfilling their implicit needs that may not be satisfied through cash-back rewards or discounts (ibid.). Although attitudinal loyalty is often valued more highly in rewards programs than its behavioural counterpart, many researchers in marketing stress the importance of taking both types of loyalty into account and endorse the belief that a firm can achieve ‘true’ loyalty by increasing the behavioural and attitudinal loyalty of its most desirable customers (ibid.).
While the use of the term “loyalty” to describe these rewards programs implies that companies can achieve – or at least strive for – perfectly loyal subjects, Andrew Smith and Leigh Sparks point out that “Loyalty is not an uncontested subject. It is partial and ambiguous and occasionally contradictory,” (2004:379). The fact that numerous consumers are members of many loyalty programs and often vary in their purchasing habits over time exemplifies the ambiguous nature of consumer loyalty (Pridmore 2010b). Furthermore, countless customers will switch to a competitor company if they can offer a better service, price, or location (ibid.). The findings from the 2011 COLLOQUY Cross-Cultural Loyalty Study demonstrate a sense of scepticism toward loyalty programs among North American consumers. When asked whether “it pays to be loyal to your favourite brands,” only twelve percent of American respondents and ten percent of Canadians replied that they “strongly agree,” (Hlavinka and Sullivan 2011). Nevertheless, these programs utilize CRM strategies to ensure a certain level of loyalty in their members and generate profit.

To guarantee that their rewards programs will be profitable, companies try to implicate consumers in a “spin cycle” of repeated shopping and responding to deals because it produces “the ultimate level of profitability,” (Lury 2004:134). Loyalty marketers assess the profitability of individual consumers using Customer Lifetime Value (CLV), which is defined as the “measure of expected value of profit to a business derived from customer relationships from the current time to some future point in time (usually three years in the case of most businesses),” and determines a maximum dollar value that can be invested in a loyal customer without overspending (Kumar and Shah 2004:322). This functions as an estimate of risk, as it denotes the probability that a company will regain its expenses in establishing and sustaining a relationship with a specific customer (Pridmore and Lyon 2011). For instance, a customer with a CLV of
$250 and a high risk of attrition can be offered incentives amounting to a maximum value of $250 in order to uphold their loyalty (ibid.). By creating detailed profiles of individual consumers that can be used for personalized marketing or sold to other companies (CIPPIC 2006), corporations use the data gleaned from loyalty programs to maximize the profits that they can gain from their existing customers.

**Potential Consequences of Loyalty Marketing: Data Mining, Social Sorting, Price Discrimination and Third Parties**

Loyalty marketers employ data mining to learn more about their customers, meaning that computerized techniques are used to obtain consumer information from sizeable databases. Using these automated techniques, marketers can discover specific facts, patterns, and relationships in mass amounts of data and make practical, informed business decisions based on the information gathered (Cavoukian 1998). The foremost functions of data mining are to enhance customer acquirement and retention; to decrease fraud; to detect and improve internal inadequacies; and to map Internet activity (ibid.). One of the loyalty marketing executives interviewed for this research described the numerous pieces of information that are stored in his company’s databases and can be extracted using data mining practices:

Let’s start with when it is transacted in the store. What we obtain is the location the transaction happened; the date that the transaction happened; the amount of purchase or proxy thereof – in other words we will sometimes just get the base [amount of points] that were issued . . . And we will receive any bonus offers, so . . . we would have a promotion code which would indicate which promotion the consumer took advantage of. Those are the basic elements we receive at the point of transaction . . . When the customer enrols we clearly have a name and address . . . We would also ask a variety of demographic and socio-demographic questions . . . We may also send out supplementary questionnaires which we would use to append information to their files . . . And then we would also track any interactions that they have with us, so . . . if they go to the website and log in, we can then track what pages they are viewing online, and if they call customer care there’s a record of the fact that they called in and something around the conversation, so we have a call history of their contact with the company.
By collecting various types of consumer information such as demographics, economic status, and geographic details, loyalty marketers can classify various segments of consumers and group them according to their shared interests, shopping patterns, and demographic qualities.

Additionally, the ability of data mining technology to accomplish these main purposes is significantly amplified through the utilization of data warehouses, where information from several different databases is merged and administered from one central database (Cavoukian 1998). As another interview participant confirms, the data collected by loyalty programs impacts how a company approaches and attempts to build a relationship with a particular customer: “So, we do a lot of work around things that we call predictive modeling – being able to predict shopping behaviours so we learn that in some scenarios you are a more important customer to a particular business than [others].” Given that corporate databases are increasing in size and can potentially be combined into data warehouses, along with the fact that many companies are collecting progressively more information on each individual consumer in order to customize and segment their offers more efficiently, the data mining practices that take place in loyalty marketing construct digital representations of customers that determine how individuals are targeted and treated by businesses.

The data mining practices that occur in loyalty marketing can be conceptualized as a form of dataveillance, meaning “the systematic use of personal data systems in the investigation or monitoring of the actions or communications of one or more persons,” (Clarke 1994:83). Unlike methods of physical and electronic surveillance, dataveillance involves the monitoring of data about individuals instead of their physical entities or actions (ibid.). Accordingly, in dataveillance it is the digital persona of the individual that is constructed and observed through the accumulation and analysis of information about
them (ibid.); in the context of loyalty marketing, various demographic and transactional data from corporate databases constitute the digital persona of a given customer, which is used by companies as a proxy for the individual and is believed to be considerably accurate. Furthermore, since the personal record of a loyalty program member is constantly being updated via the customer’s transactions and interactions with the company, the digital persona is not fixed or complete. As the consumer continues to engage in an established relationship with a business through its loyalty program, their digital persona becomes increasingly detailed, allowing marketers to predict their shopping habits and entice them with deals in a more refined manner. Despite the fact that one’s consumer profile may not fully correspond to their ‘actual’ self, digital personas represent members of contemporary loyalty marketing practices and facilitate the clustering of individuals with comparable buying patterns, neighbourhoods, life stages, gender, age, incomes, and numerous other categories (Pridmore and Lyon 2011).

Using data mining software, loyalty marketers categorize the digital profiles in their consumer database and sort them into many groups in a process known as customer segmentation. A customer will usually be classified according to their observed shopping behaviour, which is then merged with demographic information to determine their current value to the program as well as their potential future value (Pearson 2012b). Though segment size varies between programs, one segment can comprise 50 to 100 thousand consumers, and a select customer can belong to several different categories (Pridmore and Lyon 2011). As an executive known as “Paul” who was interviewed for Jason Pridmore’s research on loyalty programs indicates, “[T]here is a whole list [of segments] . . . there is a value segment, there is a campaign history segment, there is a category history segment, there is a genre segment . . . there is a
frequency score, there is a RFM [recency, frequency, monetary] score . . . there is mosaic demo[graphics], there is a life stage segment, and there is age,” (2008:78). Another loyalty program executive that was interviewed for the same study reveals how customers can be segmented in more detail, in this case from a life-stage perspective, “We’ve identified, I believe 12 different life-stages that our customers are at, at any given time. This is largely inferred based on what they are buying, so if we know customers are buying diapers and baby powder we [categorize them] as parents with young kids (Pridmore 2008:125). Importantly, the segments that a customer is classified to correspond to aspects of how their relationship with the company will unfold, such as the accretion of points from the program; prospective offers or exclusive rewards; differing levels of service; and the sum of required fees (Pridmore and Lyon 2011).

Once a customer has been categorized in various ways, the algorithm uses a decision engine to identify which marketing messages will be most applicable to that particular individual (Pearson 2012b).

In a related example, Best Buy conducted a test in which it segmented its preferred customers and sent them targeted offers in attempt to persuade them to spend more and return often (Pearson 2012b). The company was able to classify four main segments of favoured shoppers that were named Barry, Jill, Ray, and Buzz: ‘Barry’ . . . is an affluent professional who demands top-shelf technology and service. ‘Jill’ . . . is a suburban mother interested in providing her kids with technology and entertainment. ‘Ray’ is price-conscious family man who wants technology to improve his daily life. And ‘Buzz’ is possibly a techie, who wants the latest in technology and entertainment (Pearson 2012b:113). After identifying four key types of customers, Best Buy instructed its employees to keep an eye out for people like Barry, Jill, Ray, and Buzz in the store so that these customers could receive better service (ibid.). As this example
illustrates, the categories and distinctions that are produced through segmentation have a significant impact on how different customers are targeted and treated by companies.

By justifying such asymmetrical transfers of consumer information to companies as allowing marketers to “listen” to the wants, needs and desires of consumers (Manzerolle and Smeltzer 2011), corporations with loyalty programs can often gain more knowledge of customer spending habits than most consumers know about themselves (Rowley 2004). Database technology allows profiles to be constructed that are likely unrecognizable to the customers themselves, simply because most people do not think about the ways in which they are profiled by corporations. Loyalty marketers seek to communicate with customers in ways that are pertinent to their personal wants and needs; in order to do so, diagnostic techniques are used that can direct the company’s attention toward specific demographics, purchasing behaviours, ethnicities, or different amalgamations of these categories (Pearson 2012b). As Jennifer Rowley states, “data miners can track lifestyles in terms of ‘what’s in the basket’” (2004:122), highlighting how companies can make a great deal of inferences about someone from their consumption behaviours.

Smith and Sparks (2004) consider these kinds of commercial data mining practices as forms of consumer surveillance and, using a loyalty card purchase record from a national retail chain in the United Kingdom, they demonstrate how companies can use shopping habits to make detailed presumptions about consumer lifestyles:

Unsurprisingly given her diet, we would suggest that Eve suffers from spots and/or bad complexion, as attested by a very high spend on blemish concealer and the occasional purchase of Clearasil. She is a large lady judging by the size of tights purchased. Eve purchases a lot of broad health and beauty products and appears to take care of her appearance . . . She suffers from hay fever . . . Eve has a boyfriend or partner and occasionally buys him aftershave and deodorant, as well as razor blades . . . Perhaps it is Eve’s nature to be highly planned and organised and this includes for
her partner. She clearly plans Christmas well in advance (cards for her parents/family in October) and the same is true for holidays (377-378).

Despite the fact that Eve’s record comprises one of the most ‘loyal’ customers in their data set, her case illustrates how everyday practices of consumption are constantly observed, recorded and analyzed, hence echoing Susanne Lace’s perception that “we are all ‘glass consumers’: others know so much about us, they can almost see through us” (2005:1). In other words, practices of customer segmentation make categories of ‘belonging’ such as income, ethnicity, and purchasing habits readily observable to marketers, thus portraying the consumer as increasingly ‘known’ through the various categories that define them (Pridmore and Lyon 2011).

Arguably the most consequential effect of loyalty programs, social sorting has become endemic to contemporary surveillance societies (Murakami Wood, Ball, Lyon, Norris and Raab 2006). Since consumers are familiar with the requirement of personal information during economic transactions and are commonly rewarded for doing so through loyalty programs, “consumers are implicated into a system that perpetuates and reinforces systems of stratification, building up categories based on their participation,” (Murakami Wood et al 2006:30). Similarly, the classification and sorting of customer data are done by computerized codes which act as ‘invisible doors’ (Lyon 2003) that include and exclude individuals from participating in different activities and events. A strategic marketing ploy known as value discrimination is utilized by loyalty programs to establish tiered systems of preferred members by awarding select customers with a more eminent recognition of social status as well as superior products, discounts and services (Lacey and Sneath 2006).

Allocating a lifetime value to consumers is largely achieved using the Recency-Frequency-Monetary Value (RFM) approach, which segments preferred customers according to
high scores on each of these variables (Rowley 2004). Many firms use value alignment techniques such as RFM in attempt to make the profits received from a given customer parallel to the costs that are sustained to serve them (Reinartz 2010). Once the respective ‘values’ of individual consumers are determined, the company then engages in ‘pre-selling’, where specific kinds of customers are sent offers for sales and events that correspond to their purchasing profiles and assigned levels of value (Turow 2006b). For firms with loyalty programs, using social sorting techniques such as RFM and ‘pre-selling’ ensures that their most valuable customers are getting the best service (Reinartz 2010).

The utilization of social sorting techniques in loyalty marketing facilitates price discrimination, meaning that retailers can charge consumers different prices for the same products based on the data from their profiles (Turow, Feldman and Meltzer 2005). Since data algorithms allow companies to run customer profiles against myriad offers, marketers can identify which ones will appeal most to each individual shopper, making it possible for next-door neighbours to receive entirely different offers from the same enterprise (Pearson 2012b). Furthermore, loyalty programs measure the marketing responsiveness of their members by assigning an ‘avid’ score to each customer, which determines the marketing offers that they receive; these scores are used to segment consumers into tiers based on their value to the firm, ranging from deciles of ‘best customers’ to undesirable customers that are labelled ‘demarket’ (Pridmore and Lyon 2011). The avid score significantly impacts how offers are generated in a loyalty program because it is taken into account for all future transactions and fundamentally influences the kinds of offers that are marketed to different types of customers (ibid.).

Price discrimination is largely disputed by consumer advocacy groups, yet it appears to be completely legal as long as the price differences derive from rational practices like rewarding
loyal customers, and do not discriminate against inadmissible categories such as gender and race (Turow, Feldman and Meltzer 2005). While defenders of price discrimination argue that it is “part of a larger process through which companies get to know and serve individual customers in ways that benefit both sides,” critics tend to argue that it primarily benefits businesses and is disadvantageous to many individuals (ibid: 11). In addition, consumer advocates believe that price discrimination based on profiling routinely involves the use of customers’ personal information in ways that do not require their acquiescence, which can potentially lead to issues of privacy, decreased autonomy, misuse of data, and financial damage (ibid.).

Though it is difficult to determine whether price discrimination is always carried out for reasonable business purposes such as gratifying loyal customers, and it may seem as if those who are already socially privileged are in a better position to benefit from this system, Frederick Reichheld contends that “It is not a matter of rich versus poor. Loyal and disloyal segments exist across the whole spectrum of incomes, professions, and social backgrounds,” (1996:78). He cites the example of a bank discovering that the wealthy, high-balance customers who had been regarded as most desirable were much less loyal and profitable than they had initially thought; the wealthy customers took advantage of average pricing, would often prepay mortgages at the worst times, and were most likely to use the free options offered by fixed-rate lending and deposit products (ibid.). This case illustrates how a company rewarding customers for their loyalty with individualized discounts does not necessarily entail the perpetuation of social advantages and disadvantages, yet the exact implications of price discrimination remain relatively obscure.

Supermarkets are prime examples of how companies are increasingly adopting price discrimination techniques. Many grocery stores have implemented the Catalina database system,
which distributes different value coupons based on analyses of purchasing behaviour from loyalty cards (Turow, Feldman and Meltzer 2005). As Todd Morris, an executive vice president at Catalina explains, “If someone is in the baby aisle and they just purchased diapers, we might present to them at that point a baby formula or baby food that might be based on the age of their baby,” (Clifford 2012:4). This highlights how customers can be targeted in real-time with marketing messages that are relevant to their specific needs and desires.

Grocers like Safeway and Kroger have implemented individualized pricing schemes that use one’s shopping behaviours to develop specific prices and offers, in attempt to increase their profit margins by making customers spend more (Clifford 2012). Safeway recently asked some bloggers to test its pricing program, the results of which were documented by *The New York Times* in an article that focuses on two of the bloggers, Jennie Sanford and Emily Vanek. At a Safeway in Denver, a 24-pack of Refreshe bottled water costs $2.71 for Sanford, who has a record of purchasing Refreshe products, and $3.69 for Vanek, who usually buys Smartwater; the price difference is displayed on the Safeway Web site and is applied when the loyalty card is swiped at checkout (ibid.). In this scenario, price discrimination seems to benefit consumers as most of the people involved reported that the programs generally reflect their purchasing habits and preferences. However, a 2005 survey involving 1500 internet-using American adults found that 64% of respondents were unaware that it is legal for “an online store to charge different people different prices at the same time of day,” and 71% did not know that it was legal for an offline store to do the same thing (Turow, Feldman and Meltzer 2005:3). Moreover, the findings indicate that most participants oppose most forms of behavioural targeting and all forms of price discrimination, as 76% agreed that “it would bother me to learn that other people pay less than I do for the same products,” while 72% disagreed that it is okay for a store that they frequently
shop at to charge them lower prices than other shoppers if the company would rather keep them as a customer (ibid.).

Despite the fact that the majority of participants in the aforementioned survey generally held negative attitudes about behavioural targeting and price discrimination, it is unlikely that such views will always be upheld in practice because, for the most part, consumers are unaware that these marketing procedures are taking place and cannot discern when they are being offered a different price for a given product. Furthermore, having unfavourable attitudes toward price discrimination in theory does not negate the fact that many consumers are regularly reaping the benefits of individualized pricing schemes and enjoy receiving offers and discounts on their favourite products; Ainy Kazmi, a 35 year old mother of four from Maryland articulates this point in relation to Safeway’s loyalty program: “It’s a little bit creepy, but I figure they’re checking everything anyway. I might as well get a good deal out of it,” (Clifford 2012: 5-6). Given that this pricing system is expected to expand to other North American grocery chains and could possibly replace standardized price tags in the future, it is likely that the use of personal shopping data will continue to raise privacy concerns among consumers and advocacy groups (ibid.). Firms implementing individualized pricing models will have to rely on consumers accepting the collection of their personal data in exchange for lower priced items that they regularly consume (ibid.).

Nevertheless, there are further consequences of data mining technology beyond the disclosure of consumer information to corporations. Given that these practices of consumer surveillance and profiling generally lack human agency, as they are increasingly carried out by automated digital databases and software, there is potential for inaccuracies to be made throughout the data mining process (Gandy 2011). Moreover, merchants usually do not inform
consumers of the specific data they have collected about them, making it possible for price discrimination decisions to be made based on incorrect information (Turow, Feldman and Meltzer 2005). Erroneous or incomplete data can have negative effects, such as subjecting an individual to disrespectful treatment and exclusion (Evans 2005). Additionally, mistakes made in data cleaning can drastically change the information in a given consumer’s profile, which alters how they are categorized in the system; thus the digital portraits of consumers and the content that is recommended for them by commercial data mining technology may not be considered suitable or accurate by the consumers themselves (Danna and Gandy 2002). Oscar Gandy articulates the problematic nature of this issue especially well: “how does a consumer begin to challenge the accuracy of a credit score, or more critically, a prediction regarding the probability of default, or some other determination of creditworthiness that has been based on some complex multivariate and propriety assessment tool?” (2011:178). As these data mining technologies continue to be adopted by commercial entities, the pressing question of how to determine legal accountability for harms that result from the performance of digital agents or robots will have to be addressed (ibid.).

Another major implication of the commercial surveillance employed by loyalty programs is the possibility of personal data being disseminated or sold to third parties without the knowledge or consent of the consumer. The perceived need of merchants to acquire detailed information about consumers is characteristic of the North American data brokerage industry that continually collects and trades personal data regarding the wants, needs, desires and insecurities of consumers (CIPPIC 2006). In 2006 the Canadian Marketing Association reported that the marketing community in Canada supports approximately 480 000 jobs and produces over $51 billion annually, with a majority of this economic activity requiring the gathering, examination
and distribution of customer data (ibid.). Largely due to the rapidly flourishing direct marketing industry, an extensive trade of consumer information has developed across North America (CIPPIC 2006). Third party companies specializing in database analytics, consumer profiling, multi-source data mining, and geo-demographic profiling help merchants execute CRM initiatives through the collection and selling of customer data; the distribution of various consumer lists; as well as the analysis and augmentation of commercial databases (ibid.). In addition, some American information brokers sell Canadian consumer profiles obtained through a variety of sources including public records and private investigations; the fact that the powerful US-based data brokers Acxiom Corporation and Abacus Alliance hold offices in Canada exemplifies this trend (ibid.).

While some companies prefer not to share their database information with third parties, the widespread circulation and sale of consumer data is especially alarming when considering how the United States’ 2001 declaration of the ‘war on terror’ has granted North American governments with more freedom in obtaining information from diverse sources like commercial databases that, for the most part, were not accessible to police and state security officials in the past (Perri 6 2005). More recently, the American government has displayed heightened interest in loyalty card data. Katherine Albrecht, director of Consumers Against Supermarket Privacy Invasion and Numbering (CASPIAN) recalls an instance where American federal agents acquired the loyalty card records of the men involved in the September 11, 2001 attacks to “create a profile of ethnic tastes and supermarket shopping patterns associated with terrorism,” (Lury 2004:135). Similarly, food consumption patterns have been monitored by the government in attempt to analyze the effects of genetically modified foods; these occurrences raise the issue of whether it is justifiable for third parties to access consumer data in order to investigate issues
of public health and national security (Evans 2003). On a separate occasion in the United States, a man’s loyalty card records, which revealed the recent purchase of an expensive bottle of wine, were used in court as evidence that he could afford to pay more alimony (ibid.). As these examples demonstrate, the extent to which the North American data brokerage industry makes consumer information readily available to third parties including – but not limited to – commercial, legal and government entities, poses the risk of customer data being used for alternative purposes that may inflict more direct and immediate harm to certain individuals.

**Theorizing Consumer Surveillance**

Loyalty programs can be theoretically explained as existing in a system of *liquid surveillance* that constitutes “today’s regimes of visibility and invisibility, characterized by data-flows, mutating surveillance agencies, and the targeting and sorting of everyone” (Lyon 2010:326). Adapting Bauman’s theories of consumerism and liquid modernity to a surveillance context, David Lyon employs his concept of *liquid surveillance* to illustrate “the transformation of ordinary citizens into suspects and their relegation to consumer status across a range of life-spheres,” (ibid.). His idea that contemporary surveillance has the ability to creep, flow, morph, and mutate across local and global environments (ibid.) relates to how commercial surveillance technologies can facilitate the widespread availability and sale of customer data to various local and global entities, unbeknownst to most consumers. In addition, *liquid surveillance* is exemplified by the recurring flow of information between the consumer and the database, which is also experienced by members of loyalty programs through their selective “access and denial, inclusion and exclusion, privileges, rewards and benefits or lack thereof,” (ibid: 331). The shift from concrete, institutional spaces of enclosure to more fluid, flexible institutions in societies of
networks and software (ibid.) illustrates the adaptive, malleable characteristics of the database and data mining technology used in loyalty programs.

The prevalence of consumer databases has led to a shift in popular notions of consumer identity that moves away from traditional, romantic views of the independent, cohesive consumer who constructs their own identity through rational acts of consumption; today, the customer is constructed through databases that “inscribe personalities and identities onto consumers according to their discursive rules of formation,” (Zwick and Dholakia 2004b:222). In this way, the construction and categorization of consumer profiles depend on a company’s ability to individually view each customer, along with the system of norms and conditions that comprise the means by which the consumer is mapped by the organization; Detlev Zwick and Nikhil Dholakia articulate this point especially well when they state that “loyalty becomes a function of visibility and codeability of customer behaviour,” (2004b:220).

Consequently, the identification and monitoring of individuals by various conglomerations embodies a form of *customer branding* (Zwick and Dholakia 2004b) because the categories that a consumer is allocated to in a given database dictate how they are understood and marketed to by businesses. Loyalty cards are linked to the identities of consumers because people are increasingly identified, as well as surveilled, through the products that they purchase and consume. That being said, consumer identity in the age of database marketing is far from being uniform or fixed. Due to the fact that individuals belonging to more than one loyalty program can have different profiles in several discrete databases, consumers tend to be associated with multiple personas in the North American marketplace (ibid.). Instead of being a singular entity, the contemporary consumer is a “blended digital simulation” with several distinct identities that are constructed and developed in different ways, depending on how the databases
to which they belong are composed (ibid: 221). Not only do CRM and database marketing provide avenues for loyalty programs to learn more about their customers and effectively interact with them; they also create consumer identities through the construction of digital personas.

Gilles Deleuze notes that the codification of bodies in *societies of control* turns individuals into “‘dividuals’ and masses, samples, data, markets, or banks” (1992:5), highlighting the changing nature of consumer identity. Similarly, Kevin Haggerty and Richard Ericson (2000) speak of a contemporary intersection of previously detached surveillance systems, producing a *surveillant assemblage* that divides abstracted human bodies into discrete flows, which are then put back together in various settings as virtual *data-doubles*. The concept of *liquid surveillance* also represents the translation of the human body into data, facilitating the creation of *data-doubles* that arguably have a greater effect on people’s life chances and choices than their real selves (Lyon 2010). Resembling the contemporary consumer identity in loyalty programs, *dividuals* exist as physical bodies in the real world and multiple electronic subjects in computer databases (Murakami Wood 2009). The circulation of coded *data-doubles* in loyalty programs produces dispersed consumer identities that substitute for the real customer, of which the consumers themselves may not be aware (Poster 1996). Therefore the current prevalence of loyalty programs in Canada suggests that consumer identity is now coupled with consumption habits because the products that one purchases creates a trail of electronic memory-traces (Bogard 1996) through databases that bind members’ identities to their digital representations as *dividuals* or *data-doubles*.

While loyalty schemes can provide some consumers with a sense of prestige in order to make them feel appreciated, they can also alienate customers who the firm considers to be ‘undesirable’ by neglecting or even ‘demarketing’ them. Demarketing refers to actions that are
taken to discourage customers in general, or a specific class of customers, either temporarily or permanently (Gordon 2006). Databases are increasingly used by marketers to categorize consumers as targets or waste; those considered targets are further assessed and may receive different messages and discounts, while those deemed waste are neglected or pushed toward products that marketers regard as more suitable to their tastes or income (Turow 2011). Companies actively demarket less valuable customers in attempt to avoid the phenomenon known in the marketing world as *adverse selection*, – the notion that “the customers most likely to sign on are precisely the worst customers you could possibly find,” because they are merely searching for the best deals (Reichheld 1996:76).

The assemblage of detailed portraits of consumers through computerized databases facilitates social sorting by allowing retailers to efficiently target those who are deemed valuable to their company and ‘demarket’ the insignificant others (Gordon 2006). Though members of loyalty programs are often rewarded for behaviours that coincide with the categories that they belong to, they can also be penalized through demarketing measures such as limited service, heightened fees, and less targeted marketing, which help corporations decrease their spending on “the wrong customers,” (Pridmore 2008:104). As Joseph Turow (2011) points out, most of the calculations and data mining are conducted behind the scenes, making it nearly impossible to know what leads to the varying ways that customers are treated. The current proliferation of loyalty programs in Canada exemplifies this exclusionary aspect of social sorting because these programs tend to focus their marketing efforts and resources toward their most preferred clientele.

The categorical discrimination and sorting of consumers in loyalty programs resemble Gandy’s notion of the *panoptic sort*, referring to “a cybernetic triage’ that separates consumers
based on their presumed economic and political value,” (Gandy 1993:1-2). As a complex discriminatory technology, the panoptic sort ascertains a consumer’s economic value using a multitude of data sources that reveal an individual’s status and behaviours, and then sorts the consumer based on their estimated value (Gandy 1996). In his article “Coming to Terms with the Panoptic Sort,” Gandy states that “This process can be seen to generate a self-perpetuating, deviation-amplifying system of inequality,” (1996:152) because it targets ‘high quality’ economically-privileged people and discards the less-advantaged others, hence constituting an antidemocratic system of control (Pridmore and Zwick 2011).

Gandy’s concept of cumulative disadvantage emphasizes how social sorting technology can amplify the unequal distribution of life chances, which further restricts the opportunities of those who have historically experienced disadvantage in a society; here he is primarily speaking of “measures of socioeconomic status that are closely associated with indicators of race, ethnicity and gender” (2010:31). Mid-size and large retailers habitually categorize consumers based on several factors including gender, age and racial or ethnic background (Turow 2006b), while the availability of geo-demographic information allows the targeting of households according to income and wealth (Perri 6 2005). Digitized profiles in consumer databases often resemble traditional stereotypes that have historically represented marginalized groups because factors such as gender, race and class serve as popular markers of categorization due to their associations with other statuses and behaviours (Gandy 1996; 2006a). Many consumers benefit economically from the processes of categorization and sorting that occur in loyalty programs, as they are rewarded for having their ‘loyal’ consumer behaviours recorded; yet, others may experience cumulative disadvantage by being excluded from certain economic opportunities, which can also preclude them from related social and political possibilities (Pridmore and Lyon...
While consumers predominantly view this form of rational discrimination as having positive social results due to the loyalty rewards that they receive, most are relatively unaware of the potentially negative consequences that it can entail (ibid.).

Likewise, Zygmunt Bauman asserts that contemporary consumerism inflicts collateral damage on the *underclass*, which includes “poor people who drop out of school, do not work, and, if they are young women, have babies without benefit of marriage and go on welfare,” (2007:31). The stigma and neglect of the *underclass* in consumerist societies relates to how people deemed as ‘flawed consumers’ or ‘non-consumers’ are virtually ignored by retailers because “they are people with no market value; they are uncommoditized men and women, and their failure to obtain a status of proper commodity coincides with (indeed, stems from) their failure to engage in a fully fledged consumer activity. They are failed consumers,” (ibid: 31-32). Therefore, the database profiles of people belonging to subordinate groups may cause those consumers to be further disadvantaged through the social sorting practices that occur in loyalty programs, while certain groups, such as the *underclass*, are completely excluded.

Accordingly, one’s membership in a certain social group produces *categorical vulnerability* (Gandy 2006a) that causes some people to have a greater risk of experiencing discrimination through data mining technology; this is especially problematic because the invisibility of consumer profiling means that people are largely unaware of the ways that they are sorted and the groups to which they are assigned. Moreover, the production of consumer profiles can potentially reproduce the prejudices of data mining experts, as their biases can become embedded in the algorithms that demarcate privilege from risk (Ball et al 2009). In this respect, loyalty programs embody Gandy’s *panoptic sort*, as they amass consumer data from various sources into digital profiles, which are then sorted into categories in order to provide preferable
treatment to their most desirable customers, thus affecting people’s life chances and contributing to the cumulative disadvantage of marginalized groups.

Notwithstanding the possible risks associated with the corporate handling of consumer information, it must be acknowledged that loyalty marketing embodies a form of everyday surveillance (Lyon 2002) that characterizes the pervasiveness of data collection and identification systems in contemporary Western society. Although the term surveillance tends to be associated with threat, conceptualizing loyalty programs as such is not meant to render companies inherently sinister or exploitive. Positioning contemporary corporate-consumer interactions within the context of surveillance speaks to the way that detailed personal information is aggregated and classified in order to influence the purchasing patterns and behaviours of consumers. Similarly, the interactions between consumers and corporations through loyalty programs also resemble soft surveillance, described by Gary Marx (2006) as a system in which an audience assists in the production of data about itself with relatively little resistance. Corporate reward schemes represent a form of soft surveillance because commercial surveillance has become embedded in social practices of consumerism, hence facilitating the transfers and flows of information from consumers who regard data exchange as a basic custom of shopping (Zurawski 2011).

Both of these concepts situate loyalty marketing as a form of surveillance that has become normalized in contemporary consumerist societies. For instance, most people today carry around a multitude of credit cards, driver’s licenses, health cards, loyalty cards, library cards, and social insurance cards that are frequently used as means of identification in everyday transactions (Lyon 2002). Accordingly, loyalty programs exemplify how commonplace routines such as shopping are extensively tracked, monitored, recorded, and examined to such an extent
that it is often taken for granted (ibid.). Every transaction completed by a given consumer leaves trails and traces that exist within “a network of relationships that service us, situate us and help to organize and order our social lives,” (ibid:242). In this way, surveillance can reproduce and reinforce social divisions because it involves codes and categories that are inherently political and can have ethical implications (ibid.). However, that is not to say that the processes of surveillance and categorization occurring in loyalty programs are necessarily socially negative; they are vital to the success of loyalty marketing and serve social purposes, but are also increasingly imperceptible and overlooked (ibid.). Therefore as a form of everyday surveillance, loyalty programs illustrate how contemporary North American consumerism has come to involve a myriad of identification and classification practices that are required to participate as a consumer in society and are largely condoned by the general public.

Gendered Implications of Loyalty Marketing

An analysis of gender and social sorting is generally lacking in the dominant literature on commercial surveillance. It is important to examine the gendered aspects of this issue since, as Celia Lury (1993) argues, gender is notably implicated in consumerism and marketing. Interview participant Mark confirms this point: “When businesses are defining what their best customer base is and who their most important targets are, they must learn that one gender has more potential for profit and return of investment than another, and gender would be one of the standard lists of demographics that any good marketer would consider.” With the intensified commoditization of North American society during the mid to late-twentieth century, women became the ‘managers of consumption’ who predominantly did all of the shopping for their households (ibid.). Some argue that not much has changed today; for instance, Ann Bartow (2005) declares that women control 85 percent of spending on personal and household goods,
leading them to be targeted more by marketers, and that wealthy women aged 25 to 49 are the most sought after demographic. Maria Bailey (2008) supports this notion by reporting that as a whole, American women spend over $3.7 trillion on consumer goods and services per year and comprise the number three market in the world, with their combined spending power surpassing the economy of Japan. Additionally, according to Mom-entum, a report by social media and branded content agency Big Fuel, women constitute 82 percent of all consumer spending in the United States, with their buying power influencing such purchases as 91 percent of new homes, 93 percent of food, 65 percent of new cars, 89 percent of bank accounts, 66 percent of personal computers, and 92 percent of vacations (Goldman 2010).

However, some studies have also shown that men are assuming a larger role in shopping for the household. A study featured in DSN Retailing Today reported that males were responsible for approximately 54 percent of household shopping, while younger men were more likely to share the shopping responsibilities with their partners (Hill and Harmon 2009). In their research on gender and coupon use in the United States, Harmon and Hill (2003) found that fairly equal percentages of men and women bought products from grocery stores, restaurants, department stores and discount stores, among others, in the three months prior to the survey. Due to the increased male presence in the contemporary marketplace, it seems that men as well as women are subject to commercial surveillance and categorization.

Though women have traditionally been perceived as the primary consumers for the household, it is important to consider the role of men as well. The behaviour of male consumers living in 21st century Western society can be accounted for in relation to changing norms of masculinity. Mark Tungate (2008) suggests that today men are generally more sensitive, nurturing, interested in looking good, and keener on shopping than their predecessors. However
as loyalty marketer George points out, many men may enjoy shopping and collecting points from loyalty programs, yet the market is still largely dominated by women:

I think that there is a dynamic around the shopping experience that appeals much more to women. And I’m stereotyping because I actually love shopping and if I could do the grocery shopping I would . . . all the time because I love grocery shopping and I like to cook but it’s – guess what, I’m the anomaly in the world on the gender standpoint – not the mainstream.

George’s comment suggests that women are still a more lucrative demographic, though men are assuming a larger role in the contemporary marketplace. That being said, some of the most successful marketing campaigns have been ones that appealed to both sexes; for example, MasterCard advertisements proficiently represent life stages and milestones that are familiar to both men and women, such as one depicting a couple sending their child off to college, in order to covertly attract both sexes (Brennan 2009). While Tungate’s assertion that “Today’s young Western male is more likely to experiment with the signifiers of gender, and even with his own sexuality,” (2008:218) may be fairly accurate, it is still widely regarded as socially unacceptable for men to consume products that are excessively ‘feminine’, meaning that companies must employ covert marketing approaches to subtly appeal to both males and females (Brennan 2009).

Although the fact that women purchase the majority of household commodities is widely recognized and can be construed as common knowledge, it is less well-known that the North American advertising and marketing industries tend to be dominated by men. In the United States, approximately 90 percent of ad agency creative directors and 70 percent of top chief marketing officers are men (Barletta 2006). As maintained by Marti Barletta (2006) a major consequence of these industries being largely male-dominated is that many of the marketing tenets that were previously thought to be ‘normal’ for all adults are essentially normal for men. As a result, women were previously overlooked as consumers; it is important for marketers to
recognize that women are vastly different than men in their attitudes, preferences, priorities, and purchasing decision processes, especially in light of the fact that they constitute the majority of purchases in traditionally male categories such as cars, home computers, and consumer electronics (ibid.).

One noteworthy method that retailers employ to target specific men and women is through the tracking of major life events. Consumers experiencing major life events, such as a recent divorcee or homebuyer, are often unaware that their shopping habits and routines have suddenly become unstable, making them susceptible to interference from marketers (Duhigg 2012). That being said, a company can alter a customer’s shopping patterns for years by sending them an accurately timed advertisement during one of these moments of flux; of all major life events, this is most applicable for the arrival of a newborn baby because it signifies a period in which the parents’ consumption habits and brand loyalties are probably the most flexible that they will ever be (ibid.).

Target’s ability to identify pregnant customers and send them relevant marketing messages epitomizes how businesses can pinpoint certain life events and exploit consumer data to influence one’s purchasing patterns. Though it does not have a loyalty program, Target allocates a unique code to each customer in the form of a ‘Guest ID number’ that not only tracks what is purchased, but also whether a credit card or coupon is used; if a survey is filled out; and if the customer calls the help line, opens a promotional e-mail, or visits the Web site (Duhigg 2012). The Guest ID is also linked to demographic information including age, estimated salary, marital status, neighbourhood, and whether or not there are children in the family (ibid.). Given that birth records are often publically accessible, Target can detect when a female customer has
given birth, but by that time she is probably already being bombarded with advertisements and offers from other companies (ibid.).

Consequently, in 2002 the retailer tasked statistician Andrew Pole with developing a method of estimating when their pregnant customers were in the second trimester, so that specially designed ads could be sent to them during this time, when most expecting mothers start to purchase new things like maternity clothing and prenatal vitamins (Duhigg 2012). Using Target’s baby-shower registry, Pole and his team ran statistical tests to analyze how women’s shopping habits changed in the time leading up to their delivery dates, and were able to isolate specific purchasing patterns that signified pregnancy (ibid.). They found that several women on the registry bought more unscented lotion around the beginning of the second trimester and usually purchased larger quantities of supplements such as calcium, magnesium, and zinc during the first 20 weeks of pregnancy; additionally, they often bought a lot of unscented soap, hand sanitizers, washcloths, and large bags of cotton balls as they came closer to their due date (ibid.). Not only did this allow the data analysts at Target to predict the delivery date of a pregnant customer within a narrow time frame; it also facilitated the development of a ‘pregnancy prediction score’ that was assigned to women who bought any combination of 25 specific products that were identified as signals of pregnancy (ibid.). For instance, if a woman shopped at Target in March and bought cocoa butter lotion, a large purse that could be used as a diaper bag, along with zinc and magnesium supplements, the company could determine that she has say, an 87 percent likelihood of being pregnant and is expecting to deliver sometime in late August (ibid.). By monitoring the consumption patterns of female customers, the firm can influence their purchasing habits via focused targeting and marketing.
Target’s advertising and marketing strategies led to a public relations mishap almost a year after the implementation of Pole’s pregnancy prediction model, when a man angrily entered a store outside of Minneapolis with some coupons for maternity clothing and nursery furniture that had been sent to his teenage daughter (Duhigg 2012). Upon calling the man to apologize once more, the manager learned that the father had been unaware that his daughter was in fact pregnant and due in August (ibid.). Following this incident, Target’s marketing team began rethinking their advertising approaches, as the set of questions to be addresses changed to “how could they get their advertisements into expectant mothers’ hands without making it appear they were spying on them? How do you take advantage of someone’s habits without letting them know you’re studying their lives?” (ibid:6).

While Target can send personalized ad booklets to each of their customers, it is more difficult to do so with pregnant women, as the company is trying to sell them baby products that they may not even know they need yet (Duhigg 2012). As a solution, the firm made the ads for baby items seem more random by mixing them with ads that were not geared toward expectant mothers; as stated by an executive from Target, “We’d put a coupon for wineglasses next to infant clothes. That way, it looked like all the products were chosen by chance. And we found that as long as a pregnant woman thinks she hasn’t been spied on, she’ll use the coupons. She just assumes that everyone else on her block got the same mailer (ibid:7). Though it may seem invasive or creepy for a business to track a woman’s pregnancy in order to alter her shopping habits, Target’s strategy has proven to be successful. Target does not reveal the figures made in particular divisions, but between 2002 and 2010 the company’s revenues increased from 44 billion to 67 billion dollars, and in 2005 president Gregg Steinhafel was quoted bragging to
investors about the firm’s “heightened focus on items and categories that appeal to specific guest segments such as mom and baby (ibid.).

Given that loyalty programs use data mining and social sorting techniques to attract their most desirable customers, men and women are targeted in different ways by different programs, depending on the perceived value of their digitized profiles. Along with a host of other factors, gender undoubtedly plays a role in determining who is included in, and excluded from, certain consumer practices in loyalty programs. For instance, a program like Shoppers Optimum might specifically target women because 50 percent of Canadian women are members, while a program like Aeroplan, which claims to have 92 percent of Canadian business travelers as members, may focus their marketing efforts toward men (Pridmore 2010b). Within these gender categories, individuals can be included or excluded to a further extent based on their spending patterns and other demographic factors such as socioeconomic status, race, ethnicity and age. Nevertheless, these speculations remain unconfirmed due to large gaps and discrepancies in the existing literature on gender and loyalty programs. This research will contribute to the current body of literature by analyzing whether statistically significant patterns exist between men and women in their memberships in and attitudes about loyalty programs. Variables such as age, income, region, education, and race/ethnicity will also be analyzed to examine the effect of other demographic factors.


Chapter Three

What the Data Say, and Do Not Say, About Gender and Loyalty

When I first began research on this topic, I wanted to find out if the interaction of demographic categories such as gender, age, income, education and race/ethnicity contributes to cumulative disadvantage. I soon realized that constraints on time and resources would prevent such a comprehensive study, so I shifted my research question to cover some related issues within the gender and consumer surveillance niche. Specifically, I wanted to find out if there are significant gendered differences in Canadians’ participation in loyalty programs and attitudes about them, and if other demographic categories have a noteworthy effect.

The purpose in pursuing this research was to generate an analysis of loyalty marketing that could serve as an exploratory introduction to the gendered implications of consumer surveillance. I conceptualize corporate loyalty marketing practices as types of everyday surveillance meaning “a focused attention to personal details aimed at exerting an influence over or managing the objects of the data, or ‘data subjects’,” (Lyon 2002:242). I believe that a thorough sociological understanding of loyalty marketing in contemporary Canadian society must account for the corporate marketing practices and the consumers who are influenced by them.

The quantitative analysis investigates if membership in and attitudes to loyalty programs vary at statistically significant levels, depending on the demographic categories to which one belongs. In order to incorporate a business perspective, two semi-structured telephone interviews were conducted with loyalty marketing executives. This study population was very difficult to access and even harder to set up interviews with, which is why I ended up interviewing only two executives. The interview findings supplement the statistical findings and are intended to provide
a basic understanding of how loyalty marketers explain their work, along with the ways that demographic information can influence marketing practices and strategies.

**The Globalization of Personal Data (GPD) Survey**

Most of the evidence for this research derives from a statistical analysis of the 2006 Globalization of Personal Data (GPD) survey conducted by lead researcher Elia Zureik, along with his colleagues of The Surveillance Project at Queen’s University. It involved 9,606 respondents from Brazil, Canada, China, France, Hungary, Japan, Mexico, Spain and the United States, who answered questions regarding the surveillance of citizens by governments, corporations, employers, and technologies (The Surveillance Project 2008). The survey was conducted using mostly telephone, along with some face-to-face and online, interviews, and was preceded by background reports and qualitative focus group interviews in the above countries (ibid.). It is comprised of approximately 50 questions dealing with participants’ attitudes about issues like consumer surveillance, racial profiling at airports, terrorism and security, national ID cards, CCTV, media coverage of surveillance issues, workplace privacy, knowledge of privacy regulations, knowledge of various technologies, actions taken to protect information, control over personal data and public trust in government and private companies (ibid.).

Respondents from Canada, United States, France, Spain, and Hungary were screened to guarantee nationally representative samples based on gender, age and regional distribution (The Surveillance Project 2008). Although the data is a few years old and somewhat hard to interpret, the GPD survey was chosen for this research because it was readily accessible and includes questions about loyalty programs. It also has a relatively large Canadian sample size of 1001 participants. By statistically analyzing the GPD data in this way, this research can uncover
relationships between the demographic backgrounds of Canadian consumers and their participation in, as well as attitudes about, loyalty programs and commercial surveillance.

**Dependent Variables**

My analysis focuses on the questions in the “Consumers” section, namely question 27, which asks respondents to indicate the amount of customer rewards programs that they collect points or rewards from; question 28, which asks respondents to report how acceptable they think it would be for a business to use information from their consumer profile to inform them of products or services; and question 29, which asks how much say a given consumer has in what happens to their personal information after signing up for a rewards program (The Surveillance Project 2008). The literal questions used in the survey are presented in Appendix B. While questions 27 and 28 were asked to all participants, a random selection of 50 percent of respondents were asked to answer the vignette in question 29, thus the sample size for question 29 is roughly half of the overall Canadian sample size.

The specific questions that were chosen for analysis measure Canadians’ rates of membership in loyalty programs, as well as their attitudes regarding consumer information being collected and used by companies. Question 27 (“How many customer reward programs do you collect points or rewards from?”) measures the amount of loyalty programs that respondents belong to using an interval/ratio level scale ranging from 0-20. Since the frequencies of the categories exceeding three programs were significantly smaller, those who collect points from more than three loyalty programs were combined into two groups labelled “4-8” and “9-20+” in order to increase the frequencies of these categories. By running tests of significance between question 27 and the independent variables, it can be determined if statistically significant differences exist in the membership rates of the various categories in each demographic variable.
In other words, statistically significant patterns in the responses to question 27 can reveal if some demographic groups of Canadian respondents tended to belong to more or less programs than others. Therefore, question 27 was included in this study because it can be used to detect demographic patterns in loyalty program membership by providing a general understanding of the groups that tended to belong to the most, and the least, amount of loyalty programs in the survey.

The other two dependent variables under analysis are measured at the ordinal level using attitudinal scales. Question 28 ("How acceptable would it be for a business to use information from your customer profile to inform you of products or services?") measures the attitudes of consumers toward corporate data mining practices through the indication of a degree of acceptability on an ordinal scale that is coded as such: 1 – “Not acceptable at all,” 2 – “Somewhat Unacceptable,” 3 – “Somewhat Acceptable,” 4 – “Very Acceptable”. Running tests of significance with question 28 and the independent variables under examination can detect if certain demographic groups tended to have more or less favourable attitudes about consumer data being used by businesses than others. Furthermore, the findings can be compared to those from question 27 to see if the participants who tended to belong to more programs were also more likely to believe that it is very acceptable for their information to be used by businesses, and vice versa. Therefore, question 28 was included in this research to determine if statistically significant patterns exist in the attitudes of Canadian consumers regarding the acceptability of personal information being used by corporations through loyalty programs.

Question 29 ("Vignette: Mike, filling out forms for a customer loyalty card to receive a discount, to what extent does Mike have a say in what happens to his personal information?") measures the perceived control that participants believe a given loyalty program member has
over how their information is used by businesses, using an ordinal scale that is coded as: 1 – “No say,” 2 – “Some say,” 3 – “A lot of say,” 4 – “Complete say”. While question 28 measures the attitudes of the Canadian sample regarding how acceptable it is for companies to use consumer information, question 29 measures attitudes pertaining to the degree of influence or control that they believe consumers have over what happens to their information. Despite the fact that question 29 has a much smaller sample size than questions 27 and 28, it was included in the analysis because it measures a different type of attitude toward loyalty programs and can be compared to question 28 to see if the responses vary by demographics in statistically significant ways.

**Independent Variables**

The independent variables selected for this study represent demographic categories that a member of a loyalty program may be assigned to during processes of customer segmentation: gender, age, education, income, region, and race/ethnicity. It follows that these variables can influence how a given customer is approached and communicated to using targeted marketing, or demarketed if they are deemed undesirable to the company. Despite the fact that finding statistically significant differences among the independent variables in rates of membership and attitudes about loyalty programs does not necessarily mean that certain groups are being targeted or demarketed more than others, this analysis serves as a starting point to understanding how loyalty marketing is influenced by gender and other demographic factors by determining if there are significant demographic patterns in consumer participation and attitudes.

**Gender**

The variable “Gender” was measured at the nominal level using the categories (1) “Male” and (2) “Female” (Appendix B). Much of the research on gender presented in Chapter Two
suggests that women play a more influential role as consumers and are likely targeted by marketers to a greater extent than men are (Kilby and Bedwell 2005; Barletta 2006; Bailey 2008; Brennan 2009; Goldman 2010; Duhigg 2012). One of the executives interviewed for this research shared some findings on gender from a large North American privacy study that was recently conducted by his company. The results state that women are members of more rewards programs and daily deal accounts than men are, and also tend to have more password-protected online accounts, providing marketers with more potential avenues to access the personal information of women. Coinciding with the literature, I hypothesize that the women surveyed will tend to belong to more loyalty programs than men. This study, which must remain confidential for ethical reasons, also found that women are generally less comfortable divulging certain kinds of ‘sensitive’ information to companies they trust, while men (81 percent) are slightly more likely to agree that their personal information is an asset to marketers than women (75 percent). Therefore I hypothesize that women will be less likely to respond that it is very acceptable for businesses to use consumer information to inform them of products and services (question 28), and also less likely to believe that ‘Mike’ has complete say in what happens to his personal information (question 29).

Age

Age was measured at the interval/ratio level with the original categories “18-24,” “25-34,” “35-44,” “45-54,” “55-64,” and “65+” (Appendix B). In order to reduce the overall number of categories and make the frequencies more equal between them, “18-24” and “25-34” were combined to make the category “18-34,” and “55-64” was combined with “65+” to produce the category “55-65+.” In their report on loyalty trends in Canada and the United States, Kelly Hlavinka and Jim Sullivan (2011) note that rates of membership in loyalty programs have
dramatically increased among American seniors, with 54 percent participating in loyalty programs as of 2007, 61 percent in 2009, and 81 percent in 2011. However, since participation in Canada has remained relatively constant over time, with a small increase among seniors (ibid.) I hypothesize that older Canadians (ages 45 to 65 plus) will belong to less loyalty programs than the younger categories.

Barletta’s contention that marketers tend to “assume that the youth market is the market that truly counts,” (2006:262) suggests that younger adults may participate in more loyalty programs because marketers are specifically trying to appeal to consumers in early to mid adulthood. In a survey conducted by Ipsos-Reid examining “The Personal Information Canadians give to Retailers,” (2008) respondents aged 18 to 34 years were more likely than the older categories to have provided their date of birth and e-mail address when signing up for a rewards card. Additionally, a survey on “Canadians and Privacy” carried out by EKOS Research Associates (2009) found that Canadians aged 65 years and older tend to be less comfortable with disclosing personal information through loyalty programs (35 percent) and online transactions (43 percent) than the rest of the study population. This leads me to hypothesize that Canadian seniors aged 65 and over will be less likely than the reference category of 18-34 to respond that it is very acceptable for businesses to use consumer information, and that ‘Mike’ has complete say in what happens to his personal information after joining a rewards program.

Education

Education (“What is the highest level of formal education that you have completed?”) was measured at the ordinal level using the categories (1) “Grade school or some high school,” (2) “Complete high school,” (3) “Complete technical or trade school/community college,” (4) “Some community college or university, but did not finish,” (5) “Complete university degree,
such as Bachelor’s,” and (6) “Graduate degree, such as a Master’s or Ph.D.” (Appendix B).

These six categories were transformed into three broader categories coded as (1) “Grade school to high school,” (2) “Some/complete technical/trade school/community college/some university,” and (3) “Complete university degree to graduate degree.” Research has found that Canadians with a university education or higher are most likely to have signed up for a loyalty card in the past (Ipsos-Reid 2008). In light of this, along with the finding from the 2009 EKOS study that Canadians with higher levels of education tend to be more comfortable with sharing personal information in the context of loyalty programs and shopping online, I hypothesize that Canadians with a university education will tend to belong to more programs and have more favourable attitudes about the utilization of customer information than the other two categories.

In relation to question 29, research by Turow, Feldman and Meltzer found that “of all characteristics in people’s backgrounds, having more years of education is the best predictor of understanding basic realities about power to control information on them and the prices they pay when shopping online and offline,” (2005:5). Therefore I hypothesize that respondents with a university education will be less likely to believe that ‘Mike’ has complete say in what happens to his information. Nevertheless, they also point out that having more formal education does not inevitably translate into having a thorough understanding of corporate practices such as targeted marketing and price discrimination; although participants with graduate school or more scored the highest on the test provided, they still only averaged a score of 8.9 out of 17 or 51 percent (ibid.).

Income

Income (“Which of the following categories best describes your annual gross household income?”) was measured at the interval/ratio level, originally using ten categories coded as (1)
“Under $10,000” (2) “$10,000 to just under $20,000” (3) “$20,000 to just under $30,000” (4) “$30,000 to just under $40,000” (5) “$40,000 to just under $50,000” (6) “$50,000 to just under $60,000” (7) “$60,000 to just under $70,000” (8) $70,000 to just under $80,000” (9) “$80,000 to just under $100,000” and (10) “$100,000 and over” (Appendix B). This variable was transformed to create three larger categories that represent general tiers of income, labelled “Low income” (under $10,000 to just under $30,000), “Middle income” ($30,000 to just under $70,000), and “High income” ($70,000 to $100,000 and over). The categories were combined to simplify the analysis and make it easier to see significant differences between the three major levels of income.

According to Maritz Canada’s 2012 Loyalty Report, rewards programs are significantly more influential among mass-affluent consumers, defined as those who individually earn at least $125,000 annually (Daniel and Davies 2012). Not only did it find that Canadians with higher incomes belong to more programs; they also are more likely to recognize that loyalty programs “influence their consumer behaviour in overt ways such as long-term loyalty, the places to shop at and the brands one buys,” (ibid:3). Correspondingly, the aforementioned Ipsos-Reid (2008) study reports that Canadians with incomes exceeding $60,000 a year are most likely to have joined a loyalty program in the past. This leads me to hypothesize that respondents belonging to the “high income” category will tend to belong to more loyalty programs than those with “low” and “middle” incomes. In addition to education having a positive relationship with comfort levels in disclosing personal information through online shopping and loyalty programs, a similar relationship was found to exist with income (EKOS 2009), thus I hypothesize that high income individuals will be more likely than the low and middle income categories to believe that
it is acceptable for businesses to use consumer information, and that ‘Mike’ has complete say in what happens to his information.

Region

Region was measured at the nominal level using the categories (1) “British Columbia,” (2) “Alberta,” (3) “Manitoba/Saskatchewan,” (4) “Ontario,” (5) “Quebec,” and (6) “Atlantic Provinces,” (Appendix B). Since “Alberta” and “Manitoba/Saskatchewan” had relatively low frequencies and are located in the same general region of Canada, they were combined to produce the category “Prairies,” hence giving the variable five categories instead of six.

According to Ipsos-Reid (2008), urban dwellers are more likely to belong to at least one loyalty program than those inhabiting rural areas; more specifically, residents of British Columbia are more likely than those living in Atlantic Canada to have signed up for a loyalty card in the past. Therefore I hypothesize that participants residing in provinces with large urban centres like Ontario, British Columbia, and Quebec will belong to more loyalty programs than those from the prairies and Atlantic Provinces. Moreover, findings from the same study indicate that Ontario residents are more likely than residents of Quebec, and in some cases Alberta and British Columbia, to have disclosed their name, address, postal code, and e-mail address when signing up for a rewards card. This leads me to predict that participants from Ontario will have more favourable attitudes than the other regions about the collection of personal information, as well as the control that consumers have over what happens to it.

Race/Ethnicity

Race/Ethnicity (“What is your ethnic group?”) was measured at the nominal level with the categories (1) “Hispanic,” (2) “Asian/Pacific Islander,” (3) “Black/African,” (4) “Caucasian/White,” (5) “North American Indian/Inuit,” (6) “Mixed ethnic background,” and (7)
“Another population group,” (Appendix B). In view of the fact that the category “Caucasian/White” comprised approximately 85 percent of the sample, all of the other categories were combined to make the category “Other racial/ethnic groups.” Due to the deficiency of scholarly literature that examines the relationships between racial or ethnic background and loyalty programs, it would be risky to make any educated guesses or speculations concerning this variable.

**Statistical Models**

Since the questions under examination contain both ordinal and interval/ratio level variables, two statistical models were run in the analysis. The ordinary least squares model was used on question 27 to predict if there are statistically significant differences in loyalty program membership among the six independent variables. The ordinary least squares model was appropriate for question 27, as it was measured at the interval/ratio level (Long 1997). Given that questions 28 and 29 were measured at the ordinal level, an ordinal generalized linear model (Williams 2009) was employed to detect statistically significant differences in attitudes regarding the acceptability of businesses using consumer information (question 28) and how much say consumers have over what happens to their personal information (question 29). The ordered generalized linear model is based on the assumption of independence of observations, thus it was determined that this model was necessary after a Brant (1990) test indicated that the proportional odds assumption of the ordered logit model was violated for a majority of the variables. Statistical significance was conducted at the 95% confidence level for the entire analysis.

**Interviewing Loyalty Marketers**

In order to investigate the gender-specific aspects of loyalty marketing and CRM using a business-oriented perspective, this study involved two semi-structured interviews with Canadian
executives in loyalty marketing who exercised a significant degree of control in their companies. I began contacting professors in the Queen’s School of Business as well as the QSB Alumni Association to see if they could facilitate an introduction with any contacts that they had in loyalty marketing; both of the interviews were set up using this process. In order to accommodate the busy schedules of the executives, the interviews took place over the telephone and were tape-recorded. Both interviews took place during September 2012 and lasted approximately 45 minutes each. A copy of the letter of information and ethics clearance for this research was sent to the participants in advance and informed consent was verbally established at the beginning of each interview. By means of ethics agreements and letters of informed consent, anonymity has been maintained for the interviews and both interviewees agreed to have their responses recorded. Participants are referred to using fabricated names to ensure that their responses cannot be traced back to their identities.

The interviews were open-ended and exploratory in nature, aiming to gain the general outlooks of various loyalty marketers on how brand loyalty, marketing strategies, and customer lifetime value are influenced by gender and other demographics. The interviews began with general descriptions of how the program works, such as “What types of information are gathered from a customer when they scan their loyalty card at a given store?” As the interviews progressed, the questions shifted focus to more specific issues dealing with gender and demographics, like “What role does gender play in the development and implementation of your company’s loyalty marketing strategies?” A complete list of the questions used to guide the interviews is attached to this document (Appendix A). As the word “surveillance” has moderately negative connotations in contemporary Canadian society, the term was not used when interacting with loyalty marketing executives because it is not something that they want to
associate their marketing practices with. Instead, I framed my research question more broadly around wanting to look at the responsiveness of male and female consumers to the program or brand. The interview responses presented in this text have been altered to elucidate and simplify the statements given by the interviewees. For example, conversational repetition and expressions such as ‘okay,’ ‘like’ and ‘you know’ have been removed. Given the low number of interviews, the use of transcription and coding software was unnecessary. Although the findings of my research are modest and cannot be generalized, they are of interest as a preliminary exploration of the niche within which I am working.

**Findings**

As I was in line at Shopper’s Drug Mart recently, I started thinking about the various categories that data analysts could infer about me from what I was buying. At the time I was purchasing some cosmetics, face wash, deodorant, rice crackers, and a birthday card for my father. The cosmetic products could signify that I am a young woman who makes a conscious effort to look attractive. The face wash might indicate that I try to take care of my skin and may be prone to a blemish or two sometimes, while the deodorant could tell marketers about my personal hygiene or how well I maintain it. The fact that I am relatively conscious of what I eat could be deduced from my purchase of rice crackers. Lastly, it could be concluded that I like to give gifts and have a reasonably close relationship with my family from the birthday card. I wondered what else the marketers at Shopper’s could possibly know about me from my years as an Optimum member, since one basket full of goods already said a lot about me. The thought of marketers analyzing my personal information and purchasing habits made me uncomfortable, yet when asked if I had an Optimum card, I obliged anyway and scanned my card to get the points. Leaving the store, I pondered the relationship between consumer attitudes and behaviours,
finding it especially interesting that my negative attitudes did not prevent me from participating in the program. Thus in addition to investigating if participation in and attitudes about loyalty programs vary significantly between different demographic groups, I will also question if there are consistent or inconsistent patterns between the consumer attitudes and collecting behaviours of certain groups. The following section presents the findings of my statistical analysis, using supplementary evidence from interviews with marketing executives.

**Descriptive Statistics**

Table 1 presents the descriptive statistics of the variables under examination. Out of the 1,001 Canadians surveyed in the 2006 GPD opinion poll survey, slightly more than half (55 percent) reported that they collect points from one to three rewards programs, while about 36 percent do not use any loyalty cards and the remaining nine percent use between four and twenty cards. In regards to question 28 (“How acceptable would it be for a business to use information from your customer profile to inform you of products or services?”) the majority (43 percent) of the sample responded that it is somewhat acceptable, while 30 percent believed that it is not acceptable at all and 21 percent thought it was somewhat unacceptable. A minority (7 percent) of the Canadian sample responded that it was very acceptable for consumer profiles to be used by corporations. Additionally, in response to question 29 (“To what extent does [Mike] have a say in what happens to his personal information?”) most participants (41 percent) reported that he has no say, approximately 27 percent thought that he has complete say, and 22 percent believed that he has some say, with only about nine percent reporting that he has a lot of say.

<table>
<thead>
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<th>Gender</th>
<th>Observations</th>
<th>%</th>
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</thead>
<tbody>
<tr>
<td>Male</td>
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<td>47.85</td>
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<tr>
<td>Female</td>
<td>522</td>
<td>52.15</td>
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Table 1: Descriptive Statistics of Variables Included in the GPD Study
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<thead>
<tr>
<th>Province</th>
<th>Total</th>
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<tbody>
<tr>
<td>BC</td>
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<table>
<thead>
<tr>
<th>Age*</th>
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<tr>
<td>18-34</td>
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<td>35-44</td>
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<td>45-54</td>
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<td>Grade school to high school</td>
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<tr>
<td>Some/complete technical/trade school/community college/some university</td>
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<td>Complete university degree to graduate degree</td>
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<td>33.07</td>
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<tr>
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<table>
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<tr>
<th>Income*</th>
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<tbody>
<tr>
<td>Low income</td>
<td>211</td>
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<tr>
<td>Middle income</td>
<td>371</td>
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<td>High income</td>
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<th>Loyalty program membership*</th>
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<td>0</td>
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<td>36.19</td>
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<td>1</td>
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<td>10-20</td>
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<th>Acceptability of businesses using information from consumer profile*</th>
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<tbody>
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<td>29.94</td>
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<tr>
<td>Somewhat unacceptable</td>
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<td>20.78</td>
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<tr>
<td>Somewhat acceptable</td>
<td>382</td>
<td>42.68</td>
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<tr>
<td>Very acceptable</td>
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<td>6.59</td>
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</table>

<table>
<thead>
<tr>
<th>Extent of say that [Mike] has in what happens to his personal information*</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>No say</td>
<td>201</td>
<td>41.10</td>
</tr>
<tr>
<td>Some say</td>
<td>109</td>
<td>22.29</td>
</tr>
<tr>
<td>A lot of say</td>
<td>45</td>
<td>9.20</td>
</tr>
<tr>
<td>Complete say</td>
<td>134</td>
<td>27.40</td>
</tr>
</tbody>
</table>

*Total number of people surveyed

*Missing cases and those who refused or responded “don’t know” have been excluded
The other summary statistics indicate that most participants were sampled from Ontario and Quebec, which coincides with the national population distribution as they are the most populated provinces in Canada. Of those recruited for the survey, the majority were between the ages 18 to 34 (30 percent) and 55 to 65 plus (29 percent). Most respondents were moderately educated, as approximately 38 percent had attended technical/trade school or community college, and 33 percent had completed a university or graduate degree. An overwhelming majority of the sample (85 percent) indicated “White/Caucasian” as their racial/ethnic identity. In terms of income, 43 percent of the sample earn annual incomes ranging from $30,000 to just under $70,000 and were categorized as “middle income” for the purposes of this research. A slightly smaller group (32 percent) constituted “high income” individuals, earning $70,000 to $100,000 plus per year. Therefore, though most of the frequencies for the categories of each independent variable are fairly even, there is an underrepresentation of Canadians in the “low income” category, along with those who do not identify as white or Caucasian.

**Question 27**

For question 27 all of the independent variables under examination except race/ethnicity were found to be statistically significant in at least one of their categories (see Appendix C for tables with statistically insignificant results). Table 1f (Appendix C) shows that other racial/ethnic groups were found to collect points from more loyalty cards than participants who identified as white or Caucasian, but the difference between them was not statistically significant. Therefore, race/ethnicity is not an influential variable when predicting patterns of membership in rewards programs among Canadian respondents in the GPD survey.

The results of the ordinary least square model predicting membership in loyalty programs by gender are presented in Table 1a. It indicates that men tend to belong to fewer loyalty
programs than women, and the difference between them is statistically significant at the 95 percent confidence level, coinciding with my prediction from Chapter Three that women collect points from a greater number of different loyalty cards than men. This finding was confirmed in the interviews conducted for this research. When asked “What role does gender play in the development and implementation of your company’s loyalty marketing strategies?” George replies “For some time loyalty marketers have thought that loyalty programs tend to steer a little bit towards women. So, women tend to participate largely more than men in loyalty programs.” Furthermore the other interviewee, Mark, adds that “I’d say the household CEO would be in most cases the female head of household. Actually, given the nature of collection behaviour – which is often in high frequency [for] grocery and pharmacy categories – the individual driving that is quite often the female head of household.” The statistical results presented in Table 1a, along with the testimonies of the marketing executives, suggest that a gendered pattern exists in the amount and frequency of participation in loyalty programs, with women generally participating more than men.

| Gender     | Coefficient | Standard Error | p>|t| | 95% Confidence Interval |
|------------|-------------|----------------|----|------------------------|
| Male       | -0.201      | 0.085          | 0.018 | -0.367 - -0.035        |
| Female (Reference) | -    | -              | -   | -                      |

N = 981
F(1, 979) = 5.63
Prob > F = 0.018
R-squared = 0.006
Adj R2 = 0.005
Root MSE = 1.323
Correspondingly, women are particularly profitable consumers when it comes to loyalty and referrals (Barletta 2006). Since women tend to be more demanding when making an initial purchase, they often regain their invested time by staying more loyal to the brand and tend to recommend salespeople or brands that they have favourable experiences with to others (ibid.). This observed pattern of brand loyalty among women is illustrated by how they are not only the fastest growing segment of top-tier flyers in American Airlines’ loyalty program, but also exemplify their most ‘loyal’ customers (ibid.). Women outnumber men in the percentage of members who rate the program’s service as “excellent”; rate the “Value for Money” as relatively high; would “definitely recommend” the program to others; and state that they prefer American to other airlines (ibid:123). This trend seems to persist outside North America as well. In the United Kingdom, Target Group Index (TGI) research has revealed that female “main shoppers” are 25 percent more likely than the general population to report that loyalty cards are the fundamental factor when deciding what stores to shop at; this statistic nearly doubles for women who are members of both the Nectar and Tesco programs, with 44 percent regarding loyalty cards as a key influence of where they shop (Kilby and Bedwell 2005). As these findings indicate, women seem to be an extremely valuable customer segment and would be expected to receive more focused attention from loyalty marketers.

Age was also found to be a significant variable in relation to participation in loyalty programs. According to Table 1b, Canadians aged 35 to 44 years tend to belong to more loyalty programs than the reference category (18 to 34 years) and the difference between them is statistically significant. On the other hand, participants of the ages “45-54” and “55-65+” were found to belong to less programs than the reference category, but these categories are not significant at the 95 percent confidence level. Although these results appear to contradict th
Table 1b: Ordinary Least Square Model of Loyalty Program Membership by Age

| Age       | Coefficient | Standard Error | p>|t| | 95% Confidence Interval |
|-----------|-------------|----------------|-----|-------------------------|
| 35-44     | 0.237       | 0.118          | 0.045| 0.006 - 0.469           |
| 45-54     | -0.416      | 0.124          | 0.737| -0.284 - 0.201          |
| 55-65+    | -0.083      | 0.111          | 0.452| -0.301 - 0.134          |
| 18-34 (Reference) | -  | -  | -  | -                      |

N = 979  
F(3, 975) = 2.69  
Prob > F = 0.045  
R-squared = 0.008  
Adj R2 = 0.005  
Root MSE = 1.324

The hypothesis made in Chapter Three, combining the two younger categories and contrasting them with the combined older categories produces a result that supports the prediction that was originally made. That is, respondents aged 18 to 44 years generally collect points from more programs than those aged 45 to 65 and over. A possible explanation as to why older individuals may belong to fewer loyalty programs is provided by Mark when he states that:

I do know from research that we’ve done that older Canadians do participate in programs and do so with a lot of enthusiasm and a lot of engagement. But they also tend to be overrepresented in groups of Canadians who are kind of apathetic towards loyalty programs and prefer more traditional kinds of discount programs or discount marketing, like traditional coupons.

The statistical results in Table 1b suggest that adults between the ages of 35 to 44 are the most desirable age demographic for loyalty programs. Likewise, Sharon Goldman’s article “The Mom Effect” in COLLOQUY magazine (2010) suggests that gender plays a notable role in how consumers of various ages are targeted and treated by companies. She notes that many loyalty programs have begun to specifically target mothers instead of women more generally, as they have roughly $2.1 trillion in spending power (ibid.). Not only is the influential role of women with children demonstrated by the fact that they control approximately 85 percent of household
income in the United States; a survey conducted by BSM Media involving 600 American mothers found that 72 percent would label themselves as the “Chief Financial Officer” of their family (Bailey 2008:8).

The recognition of mothers as a prime consumer audience is embodied in the ways that companies have started to specifically target them using loyalty programs. For example, Build-A-Bear’s loyalty program employs a “robust online shopping experience” that recommends products based on the personal lifestyle and gifting needs of mothers and their children (Bailey 2008:14). During 2007, the company partnered with Pulaski Furniture in attempt to make the brand appeal to its key consumer segment through the development of the Build-A-Bear Home Collection (ibid.). Like the personalized teddy bears that the Build-A-Bear Workshop is known for, this customizable line of children’s bedroom furniture facilitated an amplified level of interaction between mothers, children, and the brand (ibid.). The success of this loyalty program exhibits how customization and personalization comprise a remarkably effective strategy for attracting moms as consumers because it allows marketers to cultivate loyal relationships with its most desirable clientele, regardless of their respective lifestyles and life stages (ibid.). Once a relationship is established, moms tend to be extremely loyal customers; in the previously mentioned research by BSM Media, 90 percent of mothers reported that they will stay loyal to a brand that satisfies their expectations, while 92 percent will buy the same products or brands for home and office (ibid.). In order to foster lasting relationships with this valuable segment of women, marketers must use customer insight and long-term value propositions to gain a genuine understanding of their thoughts, attitudes, and emotions, as well as what motivates them to purchase (Goldman 2010).
Furthermore, Barletta (2006) contends that certain segments of the female market are especially worthwhile to marketers, namely the 50-plus demographic which she terms “Prime Time Women”. Whereas several marketers have traditionally emphasized younger men as the most desirable consumer segment in the field, due to factors such as their greater earning power and discriminatory income, women aged 50 years and older are a rapidly growing, highly significant segment within the female market (ibid.). She explains why “Prime Time Women” are salient to marketers particularly well: “As confident breadwinners and as chief purchasing officers for their families, they enter their prime years with a degree of market clout that previously belonged almost exclusively to older men. Boomer women are the first female cohort in history to have these characteristics,” (ibid:264). This directly contrasts with dominant stereotypes that portray older women as dull, frumpy, old-fashioned, and lonely – none of which imply that they are first and foremost consumers (ibid.). Due to their immense purchasing power and prowess in the market, 50-plus women are expected to be a highly desirable segment to marketers, as they can potentially increase their profits by targeting the “healthiest, wealthiest, most active, generation of women in history,” (ibid:273).

Another significant predictor of loyalty program participation in the survey under examination is education, as shown in Table 1c. Compared to respondents whose highest level of education consists of technical/trade school or community college, those with a university or graduate degree tend to collect points from more loyalty cards, while those with a grade school to high school education tend to belong to fewer programs. The differences between both categories and the reference category are statistically significant. This is in accordance with Ipsos-Reid’s (2008) finding that Canadians who have a university education are the most likely
Table 1c: Ordinary Least Square Model of Loyalty Program Membership by Education

| Education                        | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|----------------------------------|-------------|----------------|-----|-----------------------|
| Grade to High school             | -0.416      | 0.102          | 0.000 | -0.617 - -0.215       |
| University to Grad degree        | 0.237       | 0.100          | 0.018 | 0.041 - 0.432         |
| Tech/Trade school/Community      |             |                |      |                       |
| College (Reference)              |             |                |      |                       |

N = 978
F(2, 975) = 19.54
Prob > F = 0.000
R-squared = 0.039
Adj R2= 0.037
Root MSE = 1.302

to have joined a rewards program in the past. As the findings in Table 1c indicate, it seems that individuals with higher levels of education may have a greater propensity to participate in loyalty programs.

The results of the ordinary least square model for income are presented in Table 1d. Compared to the reference category (middle income) respondents in the low income range tend to belong to less loyalty programs, while those with high incomes tend to participate in more programs. The differences between both income categories and the reference category are statistically significant at a 95 percent confidence level. These statistics support the prediction made in Chapter Three that respondents belonging to the “high income” category will generally belong to more loyalty programs than those with “low” and “middle” incomes. When examined next to Table 1c, an income-education correlation becomes evident. That is, people with higher levels of education tend to have higher incomes and engage with loyalty programs more than those with lower levels of education and income.
Table 1d: Ordinary Least Square Model of Loyalty Program Membership by Income

| Income          | Coefficient | Standard Error | p>|t| | 95% Confidence Interval |
|-----------------|-------------|----------------|-----|--------------------------|
| Low Income      | -0.410      | 0.114          | 0.000 | -0.633 - -0.187          |
| High Income     | 0.425       | 0.104          | 0.000 | 0.220 - 0.630           |
| Middle Income   | -           | -              | -   | -                        |
| (Reference)     |             |                |     |                          |

N = 847  
F(2, 844) = 24.46  
Prob > F = 0.000  
R-squared = 0.055  
Adj R2 = 0.053  
Root MSE = 1.308

During the interviews, the participants responded rather differently when asked “What role does income play in loyalty marketing and customer segmentation?” George proclaims that income is not a significant factor influencing the marketing strategies of his company:

> We carry all socio-demographic segments with the participation in the program that we offer. There doesn’t seem to be a bias. Where you do get a bias is [in] the ability of the consumer to collect currency by virtue of their ability to . . . get a credit card. That creates a skew towards collection which favours middle to upper income households because they would tend to use financial vehicles in a more pronounced way.

Later he adds “I don’t know whether we would say there’s a socio-demographic skew to the use of offers in the program . . . Certainly the more means you have, the [greater] opportunity you have to take advantage, so there may be a natural skew in the data just because of the amount of spending that occurs.” However, Mark believes that income plays a noteworthy role in consumer engagement and participation in loyalty programs: “My argument is that more affluent Canadians tend to be better consumers, or – I think ‘better’ is the wrong word. They tend to consume more, and as a result are seeking deeper relationships with the brands they spend a lot of money with.” It is interesting to note that Mark corrects himself after saying that more affluent Canadians are better consumers, which could be read as a complementary echo to Bauman’s (2007b) notion of the underclass being ‘flawed’ consumers. Not only do George and
Mark’s divergent responses suggest that income is not necessarily a dominant factor influencing consumer participation for all rewards schemes; they demonstrate how the profiling of preferred clientele varies from program to program, depending on the specific marketing motives and strategies of the company.

In the aforementioned survey by Harmon and Hill (2003) involving 206 Americans, the grocery store loyalty card was used by 71 percent of males and 76 percent of female participants, suggesting that both women and men are profiled and sorted by these programs – albeit in different ways. Income was also found to have an effect on the gendered use of loyalty cards. Middle-income men and women, whose incomes ranged from $30,000 to $59,000, were more likely to “always” or “usually” use grocery store loyalty cards than those with lower and higher incomes (ibid.). Furthermore, while high income men were less likely to use grocery store loyalty cards, high income women were more likely to use them (ibid.). Though statistics show that the rates of loyalty program membership are fairly equal between North American men and women, Harmon and Hill’s (2003) findings demonstrate that there are gendered differences in frequency of participation, which are most evident when analyzing the interaction of gender with other demographic factors, such as income. This implies that male and female consumers are being monitored, profiled, sorted and targeted in different ways and to varying extents, based on their demographic characteristics and how recurrently they participate in loyalty schemes.

Region is the final variable that was found to be statistically significant in relation to question 27. As shown in Table 1e, compared to participants living in Ontario, those residing in British Columbia, Prairies, and Atlantic Provinces tend to belong to more rewards programs, and inhabitants of Quebec tend to participate in fewer programs. However, only the difference
between Ontario and Quebec is statistically significant. Although three out of the four region categories are statistically insignificant, the finding that participants from British Columbia, Prairies, and Atlantic Provinces tend to participate in more programs than those from Ontario counters the hypothesis from Chapter Three, which predicted that participants residing in Ontario, British Columbia, and Quebec will belong to more loyalty programs than those from the prairies and Atlantic Provinces. In addition, the hypothesis made in respect to region is disconfirmed by the fact that residents of Quebec tend to collect points from less rewards programs than those from Ontario; these findings are in opposition to those of Ipsos-Reid (2008), stating that Canadians living in urban regions are more likely to belong to a loyalty program.

**Question 28**

With respect to question 28, age, income and region were found to be statistically significant variables when predicting the likelihood of different demographic groups to respond that it is “very acceptable” for businesses to use information from a consumer’s profile to inform them of products and services that they think might be of interest to them. Though Table 2a...
(Appendix C) indicates that men are less likely than women to believe that it is very acceptable for businesses to use consumer information, the difference between the gender categories is not statistically significant. Additionally, education was not found to be a significant predictor of attitudes regarding the acceptability of businesses using consumer information; nevertheless, Table 2c (Appendix C) reveals that participants with a grade school to high school education, and those with a university or graduate degree are less likely than the reference category (technical/trade school or community college) to answer that it is very acceptable for loyalty marketers to use information from consumer profiles. Finally, respondents from “other racial/ethnic groups” are more likely than those who are white or Caucasian to think that it is very acceptable for businesses to use customer information, as seen in Table 2f (Appendix C). However the difference between them is not significant. Thus gender, education, and race/ethnicity are not influential variables in relation to Canadians’ attitudes about consumer information being used by companies through loyalty programs in the GPD survey.

Table 2b presents the results of the ordinal generalized linear model predicting attitudes regarding the acceptability of companies using consumer profiles across different age categories.

| Age       | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|-----------|-------------|----------------|-----|------------------------|
| 35-44     | -0.247      | 0.173          | 0.154 | -0.587 - 0.093         |
| 45-54     | -0.552      | 0.180          | 0.002 | -0.905 - -0.199        |
| 55-65+    | -0.224      | 0.163          | 0.171 | -0.544 - 0.096         |
| 18-34 (Reference) | - | - | - | - |

N = 894  
LR chi2(3) = 9.43  
Prob > chi2 = 0.024  
Pseudo R2 = 0.004
Compared to the reference category (18 to 34 years) those aged 35 to 44, 45 to 54, and 55 to 65 plus are less likely to respond that it is very acceptable for businesses to use information from a customer’s profile to inform them of products or services that they think would be of interest to them. This confirms my hypothesis that participants aged 65 years and older will be less likely than those aged 18 to 34 years to respond that it is very acceptable for consumer information to be utilized by corporations, but only the difference between the reference category and respondents between the ages of 45 to 54 is statistically significant.

As suggested by Table 2b, Canadians aged 35 years and older seem to have less favourable attitudes about their information being used by rewards programs than those who are 18 to 34 years old. This is consistent with Ipsos-Reid’s (2008) finding that Canadian respondents aged 18 to 34 years are more likely than their older counterparts to provide their e-mail address and date of birth when joining a loyalty program. Mark provides an explanation of these observed age-based differences when he acknowledges that:

The other thing with loyalty programs is there is an element of asking people to opt-in to a deeper relationship with the brand and as a result relinquish some of your privacy around that brand . . . And younger Canadians prove to be more open to that than older Canadians. Older Canadians tend to be more concerned with privacy than younger Canadians are.

Mark’s assertion that older Canadians tend to be more reluctant to provide personal information in loyalty programs is further supported by EKOS’ (2009) finding that Canadians aged 65 and older are more likely to be uncomfortable with divulging personal information in rewards programs and online transactions than the rest of the sample surveyed. Despite the fact that only one of the age categories in the GPD survey was found to be statistically significant, Mark’s observation as a loyalty marketer, along with the supplementary findings from other Canadian surveys suggest that an age-based pattern exists in attitudes about loyalty patterns, with younger
Canadians being more comfortable with loyalty programs using their information than older Canadians.

Another significant variable influencing the Canadian responses to question 28 is income. The results of the ordered logistic regression for question 28 and income are displayed in Table 2d. Compared to participants in the middle income category, those in the low and high income categories are more likely to respond that it is very acceptable for loyalty programs to use information from consumer profiles, and the difference between the middle income and high income categories is statistically significant. This supports the prediction made in Chapter Three

| Income          | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|-----------------|-------------|----------------|-------|------------------------|
| Low Income      | 0.113       | 0.172          | 0.511 | -0.224 - 0.451         |
| High Income     | 0.330       | 0.151          | 0.029 | 0.033 - 0.626          |
| Middle Income   | (Reference) | -              | -     | -                      |

N = 776
LR chi2(2) = 4.80
Prob > chi2 = 0.091
Pseudo R2 = 0.003

that respondents with high incomes will be more likely than those in the low and middle income groups to find it very acceptable for businesses to utilize customer information in order to inform them of goods and services. Similarly, the findings of the 2009 EKOS survey state that a positive relationship exists between Canadians’ income levels and their comfort levels with disclosing personal information in online transactions and loyalty programs, meaning that individuals with higher incomes tend to be more comfortable with providing information in these contexts. In light of these statistics, along with the fact that high income individuals were found to participate
in more programs than those in the low and middle income categories when analyzing question 27, it seems that there may be some truth to the assertion of Maritz Canada’s 2012 Loyalty Report that loyalty programs are significantly more influential to mass-affluent consumers (Daniel and Davies 2012).

Finally, the results of the ordinal generalized linear model analyzing the Canadian responses to question 28 by region are presented in Table 2e. As shown in the table, residents of British Columbia, Prairies, and Quebec are less likely than the reference category (Ontario) to respond that it is very acceptable for companies to use information from consumer profiles. On the other hand, inhabitants of Atlantic Provinces are more likely than those from Ontario to respond that it is very acceptable for businesses to use consumer information, which contradicts my prediction that participants from Ontario will have more favourable attitudes than the other regions about the utilization of personal information by loyalty programs. Similar to the results displayed in Table 1e, the only region that has a statistically significant difference from Ontario is Quebec. Accordingly, of all the Canadian participants in the GPD survey, those from Quebec

| Region               | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|----------------------|-------------|----------------|-------|-------------------------|
| BC                   | -0.046      | 0.206          | 0.825 | -0.449 - 0.358          |
| Prairies             | -0.014      | 0.183          | 0.941 | -0.373 - 0.346          |
| Quebec               | -0.318      | 0.157          | 0.042 | -0.625 - -0.011         |
| Atlantic Provinces   | 0.195       | 0.246          | 0.427 | -0.287 - 0.677          |
| Ontario (Reference)  | -           | -              | -     | -                       |

N = 895
LR chi2(4) = 6.87
Prob > chi2 = 0.143
Pseudo R2 = 0.003
are the only group with significantly divergent attitudes to Ontario regarding the use of consumer information in loyalty programs.

**Question 29**

Of the six independent variables under examination, age and region are the only ones that were found to be statistically significant for question 29, predicting the amount of say that respondents think ‘Mike’ has in what happens to his personal information after signing up for a loyalty card. In terms of gender, Table 3a (Appendix C) indicates that men are more likely than women to respond that ‘Mike’ has complete say in what happens to his information, but the difference between the two gender categories is not statistically significant at the 95 percent confidence level. Likewise though education is not a statistically significant variable for question 29, Table 3c (Appendix C) shows that participants with a university or graduate degree are less likely than the reference category (technical/trade school or community college) to respond that ‘Mike’ has complete say in what happens to his personal information, while those with a grade school to high school education are more likely to believe that he has complete say. Additionally those with low and high incomes are more likely than the middle income category to believe that ‘Mike’ has complete say but, as seen in Table 3d, the differences between the low and high income categories and the reference category are not statistically significant. Lastly, compared to white/Caucasian respondents, those belonging to other racial/ethnic groups are more likely to respond that ‘Mike’ has complete say, as indicated in Table 3f (Appendix C), however the difference between them is not significant.

The results of the analysis examining question 29 by age are displayed in Table 3b. Compared to respondents aged 18 to 34 years, those aged 35 to 44, 45 to 54, and 55 to 65 plus are less likely to respond that ‘Mike’ has complete say in what happens to his personal
information after signing up for a loyalty card. The differences between categories “45-54” and “55-65+” and the reference category are statistically significant. This confirms my hypothesis in Chapter Three, that older participants will be less likely than those aged 18 to 34 to think that ‘Mike’ has complete say in what happens to his information. Furthermore, these findings correspond with those of Ipsos-Reid (2008), stating that Canadians of the ages 18 to 34 are more likely to provide their birth date and e-mail address when joining a loyalty program; given the results in Table 3b, a possible explanation for this might be that young Canadians in this age group think they have more control over their personal information and hence are more willing to provide it to companies. Similarly, the fact that respondents in the age category “55-65+” were found to be less likely than “18-34” to believe that ‘Mike’ has complete say is consistent with EKOS’ (2009) finding that Canadians aged 65 years and older tend to be less comfortable with providing personal information through loyalty programs. Therefore there seems to be an age-based trend in the perceived level of control over personal information among adult Canadians in the context of loyalty programs, with younger Canadians generally believing that consumers have more control over their information than their older counterparts; this may be connected

| Age       | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|-----------|-------------|----------------|-----|-------------------------|
| 35-44     | -0.139      | 0.226          | 0.538 | -0.581 - 0.303          |
| 45-54     | -0.576      | 0.240          | 0.016 | -1.047 - -0.106         |
| 55-65+    | -0.615      | 0.219          | 0.005 | -1.044 - -0.185         |
| 18-34 (Reference) | - | - | - | - |
with the observed patterns in more recent research of younger Canadians being more comfortable with disclosing personal information to loyalty programs than older Canadians, especially those aged 65 years and up.

Region was also found to be a significant variable for question 29, as shown by Table 3e. Compared to residents of Ontario, participants from Quebec are more likely to respond that

| Region            | Coefficient | Standard Error | p>|z|  | 95% Confidence Interval     |
|-------------------|-------------|----------------|-----|-----------------------------|
| BC                | -0.651      | 0.304          | 0.032| -1.245 - -0.056             |
| Prairies          | -0.283      | 0.245          | 0.249| -0.763 - 0.198              |
| Quebec            | 0.483       | 0.210          | 0.022| 0.071 - 0.895               |
| Atlantic Provinces| -0.255      | 0.321          | 0.428| -0.883 - 0.374              |
| Ontario (Reference)| -          | -              | -   | -                           |

N = 489
LR chi2(4) = 19.75
Prob > chi2 = 0.001
Pseudo R2 = 0.016

‘Mike’ has complete say in what happens to his personal information, while those from British Columbia, Prairies, and Atlantic Provinces are less likely to believe that he has complete say. The only regions that differ from the reference category at a statistically significant level are Quebec and British Columbia. Thus, due to these findings I must reject my hypothesis that participants from Ontario will be more likely than the other region categories to think that Mike has complete say in what happens to his information.

In summary, the statistical findings for this research indicate that the responses to each of the three GPD questions under examination vary at a significant level with certain demographic variables. For question 27 gender, age, education, income, and region were found to be
statistically significant variables influencing how many loyalty programs Canadian respondents participate in. Region, age, and income are significant variables for question 28, influencing the attitudes of respondents regarding the acceptability of loyalty programs using consumer information to inform them of products and services. Lastly, for question 29 age and region were found to be significant in predicting the beliefs of Canadian respondents in regards to how much say ‘Mike’ has in what happens to his personal information after signing up for a rewards card. Therefore, race/ethnicity does not have a statistically significant influence in relation to the membership in, or attitudes to, loyalty programs among the Canadian respondents of the GPD survey. Furthermore, region and age are the only variables with at least one statistically significant category across all three questions.

In terms of gender and loyalty, the findings for question 27 suggest that women generally participate in more loyalty programs than men do. This raises the question of whether women are generally regarded as more loyal consumers and are targeted to a greater extent by marketers. Despite the fact that the gendered differences in the responses to questions 28 and 29 are statistically insignificant, the findings propose that men are less accepting of their information being used by loyalty programs and are more likely to believe that consumers have complete control over their personal information. The less accepting attitudes toward companies using consumer data could potentially account for the lower participation rates among males, but this does not explain why the male respondents exhibited a higher level of perceived control over their personal information. While the gendered differences in participation are consistent with the attitudinal differences in question 28, the findings for question 29 show that consumer attitudes are not straightforward, but rather unpredictable and sometimes contradictory.
Chapter Four

Discussion and Conclusion

Using a statistical analysis of questions 27, 28 and 29, the previous chapter demonstrated that there are statistically significant patterns in loyalty program membership and consumer attitudes among certain demographic groups, notably income, age, and region. This chapter will discuss the implications of the findings in relation to the overall theme of gender and consumer surveillance. I will conclude by discussing the contributions that this research makes to surveillance studies and suggesting some potential directions that future research could take, with particular focus on how a similar study of gender and loyalty marketing could be improved in future years.

Not only do the significant findings in Chapter Three reveal patterns in the responses of participants belonging to different demographic groups; they also suggest that high participation in loyalty programs does not necessarily translate into more favourable attitudes about certain aspects of them, such as the use of information from customers’ profiles and the level of control that consumers have over what happens to the information gathered about them. There are some instances where the results seem to correspond with each other, such as in regards to income. Participants in the high income category tend to collect points from more loyalty programs than those with low and middle incomes and are more likely to think that it is very acceptable for businesses to use information from customer profiles. Despite the fact that income was not found to be a statistically significant variable for question 29, high income respondents were also found to be more likely than middle income to believe that Mike has complete say over what happens to his information. Conversely, though respondents from Quebec tend to participate in fewer programs than those from Ontario and are less likely to think that it is very acceptable for
companies to use consumer information, they are more likely to believe that Mike has complete say in what happens to his personal information. In this case, belonging to fewer rewards programs and disapproving of their data collection practices does not inevitably entail an overall lower level of perceived control over what happens to customer information. As these findings indicate, certain demographic groups may have a lower or higher propensity to participate in loyalty programs and have more or less favourable attitudes about them, but whether or not this can be explained as loyalty programs targeting or offering privileged service to certain demographic groups over others cannot be determined at this point.

**Women and Men: Targets and Waste?**

Gender was only found to be significant in relation to question 27, meaning that there is a significant difference between men and women in terms of how many rewards programs they tend to participate in. The fact that women tend to collect points from more loyalty programs than men coincides with the body of literature presented in Chapters Two and Three on gender and marketing, suggesting that women are generally regarded as more loyal or profitable consumers than men and are targeted by marketers accordingly. Similarly, it is also possible that certain groups of women may not be targeted at all; rather, they might labelled ‘disloyal’ or ‘undesirable’ customers and demarked by companies. Though these generalized conclusions cannot be confirmed by the statistical analysis conducted for this research, the interview transcriptions reveal that loyalty marketers are aware of these gendered differences and take them into account in the development and implementation of their advertising strategies. For instance, George states that:

I think [there is] this shopping trip behaviour that exists out there, which is skewed and generally appeals sociologically more to women than it does to men. And when you combine that with the nature of our partners’ frequency, a lot of the sponsors that we brought in . . . tend to skew towards things which are about family purchases for
the household around kids, and [there still is] a bias around that – at least in our program – around women.

When asked to elaborate on any possible explanations for this proclaimed gender bias, he briefly discusses the relationship between gender roles and shopping:

I think it gets back to sort of traditional – albeit changing roles – but traditional roles where the frequency of collection is often driven by grocery shopping and shopping in the pharmacy. We see that the frequency in those categories in our business is highly correlated with the individual that would be doing the grocery shopping, and I would say . . . based on my experience wandering through the grocery store, [there is still] a female bias to that activity.

George’s testimony, along with the statistical results of the GPD survey and the literature reviewed for this research, propose that gender is an important factor to consider when examining consumer surveillance in loyalty programs, as women tend to participate in and engage with the programs more than men. This gender bias is evident in some of the major Canadian programs, such as those of Indigo and Shopper’s Drug Mart, that appeal more to women through their marketing and advertising schemes.

Additionally, relevant literature dealing with gender and consumer surveillance, such as the work of Jane Bailey and Valerie Steeves (2013, forthcoming) demonstrates how gender plays an influential role in other types of marketing as well, namely that which takes place on social media platforms. Marketers are aware of certain gendered dispositions and tendencies that they use to target male and female consumers. For example, teenage girls spend more time interacting with social networking sites like Facebook, while boys tend to create and upload more videos to YouTube; consequently it is quite common for girls to see dieting and plastic surgery ads on their social media pages (ibid.). Bailey and Steeves also assert that women who change their Facebook status to “engaged” report being targeted with ads for wedding photographers, weight-loss programs, and skin treatments (ibid.). This relates to how cultural notions of what it means
to be ‘male’ or ‘female’ are used by companies to attract their desired clientele. As gender undoubtedly plays a role in marketing contexts outside of the loyalty rewards industry, the gendered aspects of consumer surveillance in loyalty programs serve as one contemporary example of how men and women are continually targeted, profiled and approached by companies in different ways, depending on their shopping patterns as well as the other categories to which they are assigned.

The Significance of Age in Loyalty Marketing

In addition, the statistical findings presented in Chapter Three suggest that age is a very significant factor influencing Canadian consumers in terms of their participation in, and attitudes about, loyalty programs. More specifically there is an age-based pattern in the statistical findings, indicating that older Canadians are less accepting of their information being used by companies and are more sceptical about the power or control that loyalty program members have over their personal information. Mark accounts for this in Chapter Three when he asserts that older Canadians generally prefer more traditional forms of rewards programs and tend to be more concerned about privacy than their younger counterparts. Another possible explanation for this is that younger Canadians are more technologically savvy and accustomed to providing personal information in online and offline contexts, such as social networking sites and online shopping.

Moreover, research examining the relationship between age and gender in marketing (Barletta 2006; Bailey 2008; Goldman 2010; Duhigg 2012) shows that these two demographic categories are highly relevant to marketers, and are often used together to communicate targeted marketing messages to men and women of specific age groups or life stages. This is confirmed by George when he discusses the role that age plays in the marketing and advertising strategies of his company:
Based on what they would buy in the grocery store, we would work with our partners to change the mix of offers and even the imagery that we would put in the marketing materials in order to customize those to reflect the family situation or aging state of individuals, in order to heighten the relevance of communications. And what we know by doing this is that if you can create a much more relevant contextual environment – [for example] families with young kids – you know, [offering them] recipes . . . and tips about how to get younger children to actually eat a variety of foods, you can more than double the response rate to individual offers.

Given this statement, it can be expected that age is an important factor in the categorization of consumers and the targeting of specific segments. It is also interesting to note the language that George uses. Articulating his company’s practices as “heightening the relevance of communications” and “creating a relevant contextual environment” effectively deflects attention away from the social sorting and data-mining aspects of it, regardless of whether he is making a conscious effort to do so.

Later on in the interview, George discusses how age categories influence the types of advertisements and marketing messages that his company uses to attract different segments of consumers:

At one point, we actually had three editions of our magazine where we changed the collector magazine content and covers. So, call it [80 or] 90 percent of the magazine . . . would be constant content . . . but the other 10 to 20 percent and the cover would change based on whether we thought it was a young family, or . . . a boomer household which might have older kids, or they might be empty nesters, or . . . a young single household.

This suggests that information is not merely collected and categorized in reference to the cardholder or the person whose name the loyalty account is under; rather, many companies use purchasing records and customer information to make inferences about other members of the household in order to tailor their advertisements and communications more effectively. I recently became aware of this when I visited my parents and saw some Metro coupons that my mother had received in the mail. The coupons offered her different amounts of Air Miles for
purchasing certain products. The first thing that I noticed was how personalized these coupons were, as the items reflected specific brands that my mom frequently buys when grocery shopping like Lays chips, lactose-free milk, and Diet Coke. There were also some coupons for products that my mother commonly buys for my teenage brother such as Old Spice deodorant and Oxy acne pads. This made me think about how analyzing my mom’s age in relation to her purchasing patterns would make it evident to the marketers at LoyaltyOne that she is a mother with at least one teenage son living at home. Interestingly our neighbour’s Metro coupons had also somehow ended up in our mailbox that day. The neighbour, like my mom, is a single mother with three children of similar ages to my two brothers and me. Upon comparing the two sets of coupons, I observed that the products and brands advertised were completely different, undoubtedly representing their personal shopping patterns. I expected them to receive coupons for different products; however I was surprised to realize that the neighbour was being offered more Air Miles for using her coupons than my mother was. This resembles an instance of price discrimination, where two customers with similar household structures and demographics are offered different deals for products that they regularly consume. In this case, my neighbour was regarded a more ‘loyal’ Air Miles customer by the company and hence was offered more rewards for items and brands that she commonly buys at Metro.

**Limitations and Future Directions**

Besides the dataset utilized in my research being a few years old, a major limitation of this research is that my findings cannot be generalized to the wider Canadian population, as a sample of 1001 participants is not representative of all Canadians. Yet, as previously stated this research was intended to be exploratory in nature and serve as a starting point for future studies in the relatively under-researched field of gender and consumer surveillance. Despite the fact that
more recent surveys dealing with issues of consumer privacy among Canadians present similar findings to mine for certain variables (EKOS 2009; Ipsos-Reid 2008), it is difficult to determine whether the GPD data is sufficiently reliable at this point because comparable surveys with identical questions and samples have yet to be conducted. The validity of the survey questions employed is also questionable. Since only four options were given for the attitudinal scales of questions 28 and 29, they are merely a basic indication of consumer attitudes and do not convey the complexity of Canadians’ thoughts and beliefs about consumer surveillance and loyalty programs. Future studies aiming to explore this aspect should employ qualitative methods such as focus groups or interviews in order to get a more detailed account of consumer knowledge, attitudes, beliefs, and rationales regarding consumer surveillance.

Furthermore, the present analysis of loyalty programs in relation to a set of specific demographic variables may seem to generalize loyalty programs as having the same tactics, objectives, and desired customer base. Seeing as questions 28 and 29 of the GPD survey can also be interpreted as generalizing all loyalty programs as homogenous, it must be emphasized that they have very diverse objectives and target clientele. This point is reinforced by Mark when he states that “It’s a mistake to look at all loyalty programs and say that they’re all trying to achieve the same thing.” Future research should take this into account, perhaps by comparing and contrasting the roles that gender and other demographics play across a multitude of different programs.

In terms of the interviews, I would have liked to speak to more loyalty marketing executives from a variety of different programs; doing so would have allowed me to analyze how marketers from different companies understand and justify their categorization practices in various ways, and to look for patterns or discrepancies in their responses. However given the
limited time and resources available to me, along with the difficulty that I experienced in accessing this study population, conducting more interviews was not a feasible option. Additionally, the interviews were carried out over the telephone instead of in person, due to the busy schedules and limited availability of the interviewees. Doing telephone interviews inherently prevented me from picking up on non-verbal cues, such as gestures and facial expressions, which could have affected how I interpreted the responses. It is extremely valuable for future studies to employ interviews when studying both consumers and corporate executives; Pridmore’s (2008) insightful analysis of loyalty programs demonstrates how a variety of interviews with marketers from different companies will be particularly useful for future studies on gender and consumer surveillance.

Due to the relative deficiency of literature dealing with men as consumers and loyalty program members, this research is more focused on females and does not address both genders equally. It would be interesting for future research on loyalty programs to examine the experiences, attitudes, and purchasing habits of males, especially in light of the reviewed literature (Harmon and Hill 2003; 2009; Tungate 2008) suggesting that men are increasingly gaining prominence as consumers in the contemporary marketplace. By simplifying gender to the binary categories of ‘male’ and ‘female’ for the purposes of this research, I have excluded genderqueer individuals who do not identify as distinctly male or female. This does not reflect upon my neglect of the genderqueer population; I chose to employ a binary categorization of gender because it was defined that way in the GPD survey and I could not find any literature in my area of research that addresses genderqueer consumers. If included in a survey about loyalty programs, genderqueer respondents would statistically represent a very small portion of the Canadian population, so it would be difficult to compare them to those who identify as male or
female. That being said, this is another possible avenue for studies of gender, consumerism, and surveillance to explore in the future.

Male and female consumers in contemporary Canadian society are profiled, tracked, categorized and targeted in various ways based on their demographic characteristics and purchasing patterns. At this point it is unclear whether certain combinations of demographic factors lead to these observed patterns, or if they can be better accounted for by the increased targeting of specific demographic groups by marketing executives. My research does not allow me to make any striking claims, but it serves as a preliminary explanation of an unfamiliar field and illustrates the value of discussing gender and surveillance. Despite the fact that my findings cannot generate any profound conclusions regarding gender and cumulative disadvantage, they speak to the same system that has been scrutinized by scholars like Turow (2005; 2006a; 2006b; 2008; 2011) and Gandy (1993; 1996; 2006a; 2006b; 2010; 2011) where the rational choices of the consumer facilitate rational discrimination. Overall, it is a system of rewarding the ‘winners’ and abandoning the ‘losers’ that undoubtedly has gendered dimensions. Initially I wanted to investigate who the winners and losers are in loyalty programs by analyzing how different demographic variables interact to influence cumulative disadvantage. Though I was not able to accomplish this, it can be speculated from the patterns of convergence in these findings that certain groups of men and women, such as those who are non-white and low income, may experience cumulative disadvantage due to the categorization and sorting practices that take place in loyalty marketing. Therefore the possible occurrence of cumulative disadvantage in loyalty programs is an interesting and important issue that should be addressed in future research in order to develop an account of the relationships between different demographic variables.
Another question that remains is how the consumer behaviours and attitudes can be explained or understood in the context of loyalty marketing as consumer surveillance. My findings indicate that significant patterns in consumer attitudes may exist among certain demographic groups, but they cannot account for why they exist. Since much more has been written about gender in the sociology of consumption and consumerism, perhaps this literature can be used to link gender to consumer surveillance, as surveillance has become a necessary aspect of consumption. This highlights how surveillance has become the norm in contemporary Canadian society because it is a by-product of most activities, even seemingly mundane things like shopping. Gendered studies of consumerism could be used to help account for the linkages and disparities between consumer attitudes and behaviours by explaining why certain groups of men and women might tend to have similar or different participation and attitudinal patterns in regards to loyalty programs. Given all of this, perhaps the best way to integrate gender into surveillance studies is to integrate surveillance into gendered studies of consumerism.

Most importantly, the data presented in this study shows how future research on the subject could provide extremely valuable findings that are more generalizable if the limitations outlined in this chapter could be overcome. An ideal circumstance for future research would be to have a more recent survey with a large dataset that is representative of the Canadian population and has more questions directly dealing with loyalty programs. Not only would I ask a variety of attitudinal questions similar to questions 28 and 29 of the GPD survey; I would also include more questions about the kinds of loyalty programs that respondents belong to and how often they participate in them, in order to gain a more detailed understanding of consumer attitudes and behaviours. The survey data would be supplemented by interviews with several loyalty marketing executives from a wide variety of programs, along with a qualitative analysis
of loyalty program members using interviews or focus groups. From the survey data I would expect to find similar patterns of membership and attitudes to those presented in Chapter Three, but the findings would be much more detailed and easier to draw conclusions from because the survey would be entirely focused on consumer surveillance and loyalty programs. Additionally by including questions about the kinds of programs to which different participants belong, I would be able to detect if certain demographic groups tend to belong to specific programs. For instance, I could find out if men and women tend to participate in different types of programs, and then use the interviews with marketers and the consumer focus groups to help explain how certain programs appeal to one gender over the other. While the interviews with executives would provide a wider variety of business perspectives regarding how demographic categories such as gender, age, income, education, and race/ethnicity influence loyalty marketing, the consumer focus groups would help explain the rationales behind the patterns of attitudes and behaviours found in the survey data. Conducting such a comprehensive study would help situate the concept of cumulative disadvantage in the context of loyalty marketing because the survey results would indicate patterns in membership, attitudes, and participation in specific programs among different demographic groups, while the qualitative portion would account for these patterns from the perspectives of marketers and consumers.

Conclusion

This thesis has explored the under-researched niche of gender and consumer surveillance through an analysis of existing survey data and complementary interviews with loyalty marketing executives. I have tested whether statistically significant patterns exist in the membership in and attitudes of different demographic groups in regards to loyalty programs. Though the findings suggest that certain demographic variables, including gender, may have a
significant effect on patterns of loyalty program membership and attitudes among Canadians, further research is required. Statistical evidence, along with the testimonies of two prominent loyalty marketing executives, propose that women are foremost consumers and may be regarded by companies as more profitable customers than men. Nevertheless, these findings do not permit us to simply confirm or refute this claim. This research has also questioned whether the demographic categories that are used to sort consumers influence how individuals are targeted or demarketed by companies; however the scope and limitations of this thesis prevent the formulation of any provisional conclusions at this time. Categorizations of consumers as ‘loyal’ or ‘disloyal’ vary greatly according to the respective marketing campaigns and objectives of different companies. In some instances loyalty programs might privilege customers who are already socially advantaged while others are demarketed, yet this is not always the case. Further research is needed in order to examine whether certain corporations perpetuate social advantages and disadvantages through their targeting and demarketing practices.

As a form of consumer surveillance, loyalty marketing has the potential to generate negative consequences due to data mining, social sorting, demarketing, third parties, and price discrimination. However as I have argued in previous chapters, contemporary consumerism has come to rely on the collection, storage, and analysis of consumer information in order to function efficiently. I have conceptualized rewards programs as a type of everyday surveillance (Lyon 2002) that has become normalized in North American society and tends to be overlooked by consumers. Though there are risks associated with the ways that personal information is collected and used by loyalty marketers, the relatively recent proliferation and success of these programs suggest that they will probably become even more prevalent throughout consumerist societies in the upcoming years. Loyalty programs can be beneficial to both the company and the
customer, as long as the data collection and sorting processes are carried out responsibly by marketers. Fortunately, both of the executives interviewed for this research expressed concern about the responsible utilization of consumer data. According to Mark, loyalty programs should disclose exactly how customer information is gathered and used, allowing people to opt-in or out of the program in an “eyes-open manner”:

My argument is . . . you need to do a really good job of making it clear to people and be[ing] very, very transparent about how you are collecting the data; how you are intending to store it or keep it secure; what you are going to use that data for; and how that will add value to a particular consumer . . . I want people to opt into that relationship in an eyes-open manner, like how you walk into other relationships in an eyes-open manner, right?

Moreover George asserts that “What we’ve done is be relatively careful around the use of information over time and how we look to create value from that information for our customers. And in so doing, we’ve managed to earn the trust of those customers, that we will do something of value – or try to do something of value – with the customer information.” Although it cannot be concluded that all loyalty programs have similar philosophies in this respect, these prominent marketers seem to be aware of at least some of the potentially negative repercussions and have taken measures to diminish them.

As an exploratory study of consumer surveillance in the context of loyalty marketing, this research contributes to the relatively unaddressed field of gender and surveillance as an introductory account of how gender, along with numerous other demographic variables, can affect how personal information is collected, categorized, and utilized on a daily basis. It is intended to highlight the scarcity of literature in this field and prompt further questions for future research on gender and consumer surveillance. Loyalty marketers might find value in this research as well; my finding that patterns may exist in the membership rates and attitudes of different groups of customers can provoke further market research in order to confirm or refute
this claim. Additionally it can influence the formation of public policy that regulates data mining and consumer profiling more stringently by raising awareness of the potential risks associated with consumer surveillance. Nevertheless the foremost value of this research is as an educational resource that can stimulate discussions and future empirical examinations of important sociological issues that had remained somewhat unaddressed until now.
References


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Appendix A

Interview Questions

**Essential questions**

- What types of information are gathered from a customer when they scan their loyalty card at a given store?
  - What happens to a customer’s information after it has been collected?
- How does the data collected help you market products and brands to different identifiable segments of consumers?
- Can you describe your ideal (program name) customer?
  - Are the traits of a “loyal” customer applicable across all market segments?
- What role does gender play in the development and implementation of your company’s loyalty marketing strategies?
- My statistical findings from the 2006 Globalization of Personal Data survey indicate that men tend to belong to less loyalty programs than women
  - Can you elaborate on this finding? Have you come across similar gender differences in the market research for your company?
- How does gender interact with other demographic factors when marketing to identifiable consumer segments?
  - What role does income play in loyalty marketing and customer segmentation?
  - The findings from my statistical analysis indicate that age is also a significant factor influencing membership in and attitudes about loyalty programs. Can you tell me a bit more about how age is used in loyalty marketing?

**Time dependent questions**

- What are the challenges you face in identifying customer behaviours and attitudes with your system?
- What sorts of reactions (both positive and negative) have customers had to your program?
Appendix B

The Globalization of Personal Data Survey

E. RECORD SEX OF RESPONDENT [DO NOT ASK QUESTION. RECORD ONLY]:
WATCH QUOTAS (50/50)

Male .................................................................□ 1

Female .................................................................□ 2

F. Which of the following categories best describes your age? You may stop me when I read the correct category.

Under 18 □ terminate

18-24 □ 1

25-34 □ 2

35-44 □ 3

45-54 □ 4

55-64 □ 5

65+ □ 6

Unsure/Refused □ 9

41. CANADA: What is the highest level of formal education that you have completed?
[READ LIST]
[CUSTOMIZE ACCORDING TO COUNTRY OF INTERVIEW]

<table>
<thead>
<tr>
<th>Education Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>01 Grade school or some high school</td>
</tr>
<tr>
<td>02 Complete high school</td>
</tr>
<tr>
<td>03 Complete technical or trade school/Community college</td>
</tr>
</tbody>
</table>
44. And which of the following categories best describes your annual household income? That is, the total income before taxes – or gross income – of all persons in your household combined? Just stop me when I reach your category. READ LIST.

[INSERT APPROPRIATE CATEGORIES FOR EACH COUNTRY]
[CUSTOMIZE ACCORDING TO COUNTRY OF INTERVIEW]

<table>
<thead>
<tr>
<th>Income Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>01 Under $10,000</td>
</tr>
<tr>
<td>02 $10,000 to just under $20,000</td>
</tr>
<tr>
<td>03 $20,000 to just under $30,000</td>
</tr>
<tr>
<td>04 $30,000 to just under $40,000</td>
</tr>
<tr>
<td>05 $40,000 to just under $50,000</td>
</tr>
<tr>
<td>06 $50,000 to just under $60,000</td>
</tr>
<tr>
<td>07 $60,000 to just under $70,000</td>
</tr>
<tr>
<td>08 $70,000 to just under $80,000</td>
</tr>
<tr>
<td>09 $80,000 to just under $100,000</td>
</tr>
</tbody>
</table>
Variable q27: [q27] How many customer reward programs do you collect points or rewards from?

Literal Question:
Some companies offer customer rewards programs where you can earn points or rewards based on how often you buy something from them or use their services (for example frequent flyer programmes or [local examples like Air Miles]). How many of these types of programmes do you collect points or rewards from? If you don't belong to any, just say "none".

Variable q28: [q28] How acceptable would it be for a business to use information from your customer profile to inform you of products or services?

Literal Question:
Many businesses create profiles about their customers that include information about purchasing habits, personal characteristics and credit history. How acceptable to you would it be for a business to use information from your customer profile to inform you of products or services that they think would be of interest to you? Do you feel it is

1 Not acceptable at all
2 Somewhat unacceptable
3 Somewhat acceptable
Variable q29: [q29] Vignette: Mike, filling out forms for a customer loyalty card to receive a
discount, to what extent does Mike have a say in what happens to his personal information?

Pre-Question Text:
We are now nearing the end of the survey. Once we have completed this group of questions I
will just have a few final questions for statistical purposes. The following questions reflects a
series of situations that we would like to get your opinions on, based on the information I provide
you for each scenario. Please understand there are no right or wrong answers, we are interested
in your opinion.

Literal Question:
[Mike] goes to the drug store to buy film, which was advertised to be on sale. He finds out at the
store that in order to receive the discount, he must apply for a customer loyalty card, which
involves filling out an application form. It requires [Mike] to fill out his home address,
occupation, and marital status. He fills the form out to get the special pricing. To what extent
does [Mike] have a say in what happens to his personal information? Is it

1 No say
2 Some say
3 A lot of say
4 Complete say
8 Refused
9 DK/Not sure
Appendix C

Statistically Insignificant Tables

Table 1f: Ordinary Least Square Model of Loyalty Program Membership by Race/Ethnicity

| Race                  | Coefficient | Standard Error | p>|t| | 95% Confidence Interval |
|-----------------------|-------------|----------------|---------|-------------------------|
| Other Racial/Ethnic Groups | -0.111      | 0.118          | 0.347   | -0.343 - 0.121          |
| White/Caucasian (Reference) | -          | -              | -       | -                       |

N = 969
F(1, 967) = 0.89
Prob > F = 0.347
R-squared = 0.001
Adj R2 = -0.000
Root MSE = 1.321

Table 2a: Ordered Logistic Regression of Acceptability of Businesses using Consumer Info by Gender

| Gender             | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|--------------------|-------------|----------------|---------|-------------------------|
| Male               | -0.174      | 0.123          | 0.158   | -0.415 - 0.067          |
| Female (Reference) | -           | -              | -       | -                       |

N = 895
LR chi2(1) = 2.00
Prob > chi2 = 0.158
Pseudo R2 = 0.001

Table 2c: Ordered Logistic Regression of Acceptability of Businesses using Consumer Info by Education

| Education                          | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|------------------------------------|-------------|----------------|---------|-------------------------|
| Grade to High school               | -0.943      | 0.155          | 0.544   | -0.399 - 0.210          |
| University to Grad degree          | -0.046      | 0.143          | 0.746   | -0.327 - 0.235          |
| Tech/Trade school/Community College (Reference) | -          | -              | -       | -                       |

N = 894
LR chi2(2) = 0.37
Prob > chi2 = 0.830
Pseudo R2 = 0.000
Table 2f: Ordered Logistic Regression of Acceptability of Businesses using Consumer Info by Race/Ethnicity

| Race                     | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|--------------------------|-------------|----------------|-----|----------------------------|
| Other Racial/Ethnic Groups | 0.100       | 0.178          | 0.573 | -0.249 - 0.450          |
| White/Caucasian (Reference) | -           | -              | -    | -                          |

N = 883
LR chi2(1) = 0.32
Prob > chi2 = 0.573
Pseudo R2 = 0.000

Table 3a: Ordered Logistic Regression of Responses to Vignette (q29) by Gender

| Gender              | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|---------------------|-------------|----------------|-----|----------------------------|
| Male                | 0.188       | 0.166          | 0.256 | -0.137 - 0.513          |
| Female (Reference)  | -           | -              | -    | -                          |

N = 489
LR chi2(1) = 1.29
Prob > chi2 = 0.256
Pseudo R2 = 0.001

Table 3c: Ordered Logistic Regression of Responses to Vignette (q29) by Education

| Education                        | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|----------------------------------|-------------|----------------|-----|----------------------------|
| Grade to High school             | 0.012       | 0.199          | 0.952 | -0.377 - 0.401          |
| University to Grad degree        | -0.160      | 0.202          | 0.426 | -0.556 - 0.235          |
| Tech/Trade school/Community      | -           | -              | -    | -                          |
| College (Reference)              | -           | -              | -    | -                          |

N = 489
LR chi2(2) = 0.85
Prob > chi2 = 0.653
Pseudo R2 = 0.001

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### Table 3d: Ordered Logistic Regression of Responses to Vignette (q29) by Income

| Income            | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|-------------------|-------------|----------------|-----|------------------------|
| Low Income        | 0.001       | 0.226          | 0.995 | -0.443 - 0.445         |
| High Income       | 0.059       | 0.207          | 0.776 | -0.347 - 0.466         |
| Middle Income (Reference) | -           | -              | -    | -                      |

N = 419  
LR chi2(2) = 0.10  
Prob > chi2 = 0.953  
Pseudo R2 = 0.000

### Table 3f: Ordered Logistic Regression of Responses to Vignette (q29) by Race/Ethnicity

| Race                  | Coefficient | Standard Error | p>|z| | 95% Confidence Interval |
|-----------------------|-------------|----------------|-----|------------------------|
| Other Racial/Ethnic Groups | 0.158       | 0.240          | 0.948 | -0.455 - 0.487         |
| White/Caucasian (Reference) | -           | -              | -    | -                      |

N = 484  
LR chi2(1) = 0.00  
Prob > chi2 = 0.948  
Pseudo R2 = 0.000
Appendix D

Ethics Clearance

June 05, 2012

Miss Amelia Cheston
Master’s Student
Department of Sociology
Queen's University
Kingston, ON K7L 3N6

GREB Ref #: GSOC-096-12; Romeo # 6007050 Title: "GSOC-096-12 The Price of Loyalty: Risks and Rewards in Personal Information Handling"

Dear Miss Cheston:

The General Research Ethics Board (GREB), by means of a delegated board review, has cleared your proposal entitled "GSOC-096-12 The Price of Loyalty: Risks and Rewards in Personal Information Handling" for ethical compliance with the Tri-Council Guidelines (TCPS) and Queen's ethics policies. In accordance with the Tri-Council Guidelines (article D.1.6) and Senate Terms of Reference (article G), your project has been cleared for one year. At the end of each year, the GREB will ask if your project has been completed and if not, what changes have occurred or will occur in the next year.

You are reminded of your obligation to advise the GREB, with a copy to your unit REB, of any adverse event(s) that occur during this one year period (access this form at https://eservices.queensu.ca/romeo_researcher/ and click Events - GREB Adverse Event Report). An adverse event includes, but is not limited to, a complaint, a change or unexpected event that alters the level of risk for the researcher or participants or situation that requires a substantial change in approach to a participant(s). You are also advised that all adverse events must be reported to the GREB within 48 hours.

You are also reminded that all changes that might affect human participants must be cleared by the GREB. For example you must report changes to the level of risk, applicant characteristics, and implementations of new procedures. To make an amendment, access the application at https://eservices.queensu.ca/romeo_researcher/ and click Events - GREB Amendment to Approved Study Form. These changes will automatically be sent to the Ethics Coordinator, Gail Irving, at the Office of Research Services or irvingg@queensu.ca for further review and clearance by the GREB or GREB Chair.
On behalf of the General Research Ethics Board, I wish you continued success in your research.

Yours sincerely,

Joan Stevenson, Ph.D.
Professor and Chair
General Research Ethics Board