A Close Look at the Nomology of Support for National Smoking Bans amongst Hospitality

Industry Managers: An application of Growth Mixture Modeling

A thesis submitted in fulfilment of

requirements for the degree

of Doctor of Philosophy in Psychology

at the University of Canterbury

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2007

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Abstract

Politicians and social marketers considering whether, and how, to implement a national smoking

ban in their countries require sound evidence regarding what the causes of support are amongst

key stakeholders, how this support will develop over the short to medium term in which they

seek to be re-elected, and how support relates to critical outcomes like enforcement. In response

to this need, I use structural equation models to develop a model of the antecedents of support,

based on theories of self interest and common sense justice, amongst hospitality industry

managers. I show that support is determined more by fairness related constructs than self interest

constructs, that support for national smoking bans increases consistently over time, and that the

initial level of support, and the rate at which support increases, is positively related to subsequent

enforcement behaviour by bar managers, in the year after implementation of such a ban, in New

Zealand. I use growth mixture modeling to identify two subgroups of bar managers whose

support changes at different rates. First, a class of bar managers with a high proportion of

smokers who reported fewer instances of respiratory related health problems, showed low initial

support, and whose support for the legislation slowly decreased.   And second, a class of bar

managers comprised of fewer smokers, but reporting more instances of respiratory related health

problems. This class began with a high degree support, and steadily increased in support for the

national smoking ban. I discuss the implications of these findings for social marketers, health

educationalists, and politicians interested in introducing a similar ban in other countries.

Chapter one – introduction – framing the research question

The trend of banning smoking in bars and restaurants, which began in North American cities, is now spreading to national bans covering the workplace in general (Koh, Joossens, & Connolly, 2007). Such bans, pioneered by Ireland, Norway, and New Zealand, should come as no surprise. The negative health impacts of environmental tobacco smoke (ETS) are so widely documented that the potential public health benefit of legislating against smoking in the workplace is difficult to deny (e.g. US Department of Health and Human Services, 2006; International Agency for Research on Cancer, 2002; Hill, Blakely, Kawachi & Woodward, 2004; UK Department of Health and Social Security, 1988; US Department of Health and Human Services, 1986; Taylor, Johnson, & Kazemi, 1992; Reynolds, 1999; Siegel, 1993). The first evaluations of the health impact of national workplace smoking bans have also shown that the anticipated health benefits of these bans are, in fact, realised. For example, health outcomes of hospitality workers in Ireland have improved since the Irish ban's introduction (Koh, Joossens, & Connolly, 2007). Recently reported research from Scotland has shown a reduction in heart attack related hospital admissions one year after a workplace smoking ban's introduction (BBC, 2007). Similar results have also been observed with city wide evaluations of the health impact of smoking bans (Sargent, Shepard, & Glantz, 2004; American Heart Association, 2006; Khuder, Milz, Jordan, Price, Silvestri, & Butler, 2007). Indeed, the threat to public health posed by ETS is so devastating, and the health case in favour of national workplace smoking bans so strong, that the topic has now become a key issue on the political agenda in the United States. For example, New York Senator, and presidential hopeful, Hillary Clinton, recently called the day when smoking would be banned in public places in the United States 'a good day for America' (CNN, 2007).

With questions on the health threats of smoking so comprehensively resolved, opposition to smoking bans has more recently taken the form of economic arguments (Magzamen, Charlesworth & Glantz, 2001). Yet the economic case against national smoking bans is rickety. Research findings show that the negative economic implications expected by certain business sectors in areas where bans exist, on the whole, do not occur (e.g. Glantz & Smith, 1994, 1997; Cremieux & Oulette, 2001; Glantz & Wilson-Loots, 2003; Scollo, Lal, Hyland, & Glantz, 2003; Cowling & Bond, 2005). In the rare cases where an economic downturn was experienced, declining sales trends cannot be attributed to the smoking ban. Rather, they have been shown to be a continuation of an economic trend that began prior to ban implementation (Luk, Ferrence, & Gmel, 2006). There is even evidence that suggests that elimination of workplace smoking would increase organizational effectiveness (Aronow, 1978; Ockene, 1984; Greenberg, 1994).

An immutable consequence of smoking bans is the establishment of an order of precedence regarding the rights of smokers and the health of the wider public. And, in point of fact, rights based arguments are the remaining buttress on which anti-smoking cases have tended to depend. Greenberg (1994), for example, noted that the case has been made that smoking bans in the workplace are a violation of civil liberties, with smokers being an 'oppressed minority'. The right which some believe smoking bans infringe (e.g. Hadaway & Beyerstein, 1987) is embodied in the standard biomedical ethical principle of respect for autonomy (Beauchamp & Childress, 2001) and in conventional Libertarian philosophy (John Stuart Mill, 1859/1952). Yet, while to some, smoking bans might be seen as a restriction of personal freedom, it can also be argued that these public health initiatives confer autonomy on individuals rather than remove it (Siegel & Donor, 1998). Moreover, the curtailment of smokers' rights due to smoking bans is consistent with the Mill's Libertarian philosophy, which suggests that the only acceptable

grounds for restricting individual liberties is to prevent injury to others. So, given this ineluctable preponderance of evidence and argument in favour of national smoking bans, the question for policy makers in other countries ought not to be 'should we have a national ban on smoking in the workplace?', but 'why don't we have one yet?'

The short answer is that such policies are still a cause of considerable controversy. This is perhaps partly attributable to media coverage of issues related to smoking bans. For example, Campion and Chapman (2005) suggested that 'skilled advocates try to work within the constraints required by journalists to strategically emphasise concerns they hope will define the dominant frame of meaning around an issue, and the one that key decision makers will come to share (p680)'. Their thematic analyses of tobacco industry messages about bans revealed themes implying that the health risks of ETS are exaggerated, that smoking bans result in negative economic impacts on bars and restaurants, and that smoking bans are an unjust infringement of smokers' rights. In light of much of the aforementioned evidence, many of these messages might at best be considered disingenuous. Nevertheless, selective framing of the issues around workplace smoking, I believe, causes confusion amongst the general public about what claims the available data can actually support, and confusion amongst politicians regarding what the major stakeholders affected by workplace smoking bans actually believe. In my view, if policy makers had knowledge of how the major stakeholders impacted by national smoking bans would react, and what the major determinants of support for national smoking bans were amongst these key stakeholder groups, national bans would be more likely to become widespread. The purpose of this paper is, therefore, to closely examine support for national smoking bans amongst a key stakeholder group, namely a cohort of bar managers (owner-managers and worker-managers). In

addition to tracking attitudes toward supporting the ban, I also looked at their determinants and consequences.

There have been, of course, previous studies of support for smoking bans. However, many questions about support for national smoking bans, in my view, have not yet been satisfactorily addressed. Let me clarify this point. People's reactions to bans are complex. Yet most information on support for smoking bans comes from polls assessing support from proportions responding to single item measures (e.g. Hammond, Costello, Fong, & Topham, 2006). Where more appropriate (i.e. multiple-item) psychometric measures have been used, support has still tended to be imagined as a construct in isolation (e.g. Doucet, Velicer & Laforge, 2007). But policy makers also need knowledge of the antecedents and consequences of support. Multivariate modelling of the nomology of support might even reveal how policy makers and social marketers could <u>influence</u> levels of support amongst constituents. To be intellectually compelling, models should also be informed by theories of reasoned human behaviour, and they should be empirically refutable. Multivariate modelling of these phenomena will be complex, because support for national smoking bans is likely to be dynamic. Support, therefore, needs to be modelled longitudinally, to show how it evolves with time, circumstance, and experience. Extant research eschews this fact. Rather, it has tended to look at people's <u>expectations</u> about future smoking bans (Galaif, Sussman, & Bundek, 1996; Hammar, 2004), or at cross sectional snapshots of support for existing bans (Martinez-Donate, Hofstetter, Gonzalez-Perez, Adams & Kotay, 2007). Finally, all of these research desiderata need to be applied in a microcosm likely to generalize to the national United States context. But existing research on how major stakeholders react to bans has tended to be based on city wide, or organizational level, bans.

Here, I describe a study of support for national smoking bans based on an empirical examination of what happened when such a ban was implemented in New Zealand. New Zealand is a country with a culture bearing many similarities to the United States, for example. Recent research by House, Hanges, Javidan, Dorfman and Gupta (2004) found that although a New Zealand sample scored higher on a societal institutional collectivism dimension than the United States sample, in many other respects, the two countries appeared to be very similar (see also Hofstede, 2001). New Zealand also became the third country in the world, behind Ireland and Norway, to implement a national ban on smoking in the workplace, including bars and restaurants on December 10, 2004. I will examine support for the national ban amongst a cohort of owners-managers and worker-managers of New Zealand bars and restaurants. These individuals constitute a key stakeholder group, potentially influencing both whether a national smoking ban is implemented, and how it would be enforced. Amongst this group, passive smoking has also previously been a fact of life. I expect results demonstrating the causes and consequences here are likely to generalize to the broader population, where tobacco smoke may already be deemed less socially acceptable.

First, in chapter two, I will introduce theories of self interest and justice, which have seen extensive use in researchers' explanations for reasoned human behavior. Based on these theories, I identify constructs related to legislative support, and hypothesize relationships amongst them. In chapter three, using cross sectional structural equation modeling with multiple item measures, I then examine empirical support for this theoretical model in terms of model fit; whether self-interest or justice constructs have the greatest explanatory power for determining support for the national smoking ban in New Zealand; measurement and structural invariance of my model across bar manager subpopulations of owners and worker and smokers and non-

smokers, and whether my theoretical model, first tested in the month prior to the ban, also holds across time at six months later, and again at twelve months later. In chapter four, recognizing that support is dynamic, and should be studied longitudinally, I introduce multiple indicator latent variable growth models for support and related processes identified in my cross sectional models. I model these growth processes multivariately, and with a measure of enforcement behavior, a critical distal outcome variable. In chapter five, I estimate mixture models to see whether there are subpopulations that change their support at different rates. By drawing on current theory and methodological advances from quantitative psychology in this fashion, I aim to overcome the limitations of previous attempts at studying stakeholder attitudes to smoking bans. Finally, in chapter six, I conclude with a discussion of the implications of my findings for policy makers who wish to implement a national smoking ban in their own countries.

Chapter two - developing a theoretical model of the nomology of support

As discussed in chapter one, in this chapter, I introduce theories of self interest and justice, and use them to identify constructs that are likely to determine support for the national smoking legislation amongst bar managers in New Zealand. On the basis of these two theories, I identify 14 hypotheses for empirical examination with structural equation modeling. This chapter, therefore, sets out the structure of the remaining empirical analyses in my dissertation.

Hypotheses based on self interest

Considerable research in the political sciences literature has examined conditions under which self interest is a determinant of policy and candidate preferences (e.g. Sears & Funk, 1990; Citrin & Green, 1990). Because the smoking ban in New Zealand reflects government policy, self-interest is an appealing theoretical framework to use in identifying variables causing bar managers to support the national smoking ban. Sears and Funk (1990) defined self-interest as the short to medium-term impact of an issue on the material well being of an individual's personal life, or that of his or her immediate family. They say the self-interest hypothesis rests on three assumptions. First, materialistic hedonism, or a pleasure-pain principle, drives human motivation. Second, personal outcomes are more important than the outcomes of others. Finally, human-decision making is essentially rational - a supposition Shafir and Le Bouf (2002) describe as "perhaps the most common and pivotal assumption underlying theoretical accounts of human behaviour in various disciplines" (p1). The self interest hypothesis suggests that if bar managers perceive that they will experience negative outcomes due to the legislation, they should evince lower support. On the basis of self interest, therefore, I identified two hypotheses. Hypothesis 1 is that perceptions that enforcing the smoking ban makes bar managers' jobs more

difficult will lead to lower bar manager support for the legislation. <u>Hypothesis 2</u> is that believing that the hospitality industry will experience negative economic implications due to the legislation will lead to lower bar manager support for the legislation.

<u>Hypotheses based on justice</u>

Conventional defences of smokers' rights to smoke freely, reflecting Mill's (1859/1952) Libertarian philosophy, hinge on arguments that the threat posed by passive smoking to public health is exaggerated (e.g. Hadaway & Beyerstein, 1987; vide introduction). This suggests that bar managers' beliefs about the dangers of ETS might determine whether they will consider exposing others to second hand smoke fair. By fair, I mean whether or not participants consider smoking around non-smokers contravenes distributive justice principles. I use fairness to refer not so much to 'what is', but to 'what should be'. Finkel (2000) used the term 'commonsense justice' to refer to this construct, which he described as what ordinary people think is just and fair. He found commonsense justice to be inclusive of what individuals referred to as just, to refer more to outcomes than to the processes by which those outcomes came about, and to contain a small residual component of misfortune. I expect that as beliefs in the health threat ETS poses increases, so should the extent to which bar managers and bar workers believe that exposing workers and patrons to ETS violates merit-based justice principles. Justice theory may therefore play an important complementary role to self interest in determining support.

The prominence of justice theories in research explaining attitudes and behaviour in social sciences research parallels that of self-interest theories. Cropanzano, Byrne, Ramona Bobocel & Rupp (2001) suggest its explanatory appeal stems from at least four sources. First, a just world allows more accurate determination of rewards and punishments. Second, when we are treated fairly our sense of group membership is enhanced. Third, fair treatment increases our

self regard. Finally, we want to have meaningful lives, and to feel as though we are "virtuous actors in a just world" (p. 178, Cropanzano, Byrne, Ramona Bobocel &Rupp, 2001). Moreover, the justice framework has already seen extensive use by researchers trying to explain attitudes in controversial contexts, such as in the affirmative action domain. For example, along with self-interest, the primary theoretical lens used by Harrison, Kravitz, Mayer, Leslie & Lev-Arey (1991) to synthesize more than 30 years of research on employee attitudes towards AAPs was justice. The parallels between AAPs and smoking bans are clear. Smoking bans have the potential to lower employee morale and divide worker opinion (e.g. Greenberg, 1994), while affirmative action policies are among the 'most controversial personnel procedures facing work organizations today' (p1168, Cropanzano, Slaughter and Bachiochi, 2005).

On the basis of distributive justice theory, I make four hypotheses.   Hypothesis 3 is that beliefs about the danger of ETS will positively predict beliefs about the injustice of exposing workers to ETS. Hypothesis 4 is that beliefs about the danger of ETS will positively predict beliefs about the injustice of exposing patrons to ETS. Within these two hypotheses, I capture the trade off between the rights of smokers to do as they choose, and the rights of the wider public to smoke free environments. Because a number of studies have also demonstrated that as people's perceptions of the fairness of Affirmative Action Policies (AAPs) decreases, so does their support for AAPs (Bobocel, Son-Hing, Davey, Stanley and Zanna, 1998), Hypothesis 5 is that if bar managers believe exposing workers to ETS is unjust, they will show higher support for the smoking ban. Hypothesis 6 is that if bar managers believe exposing patrons to ETS is unjust, they will show higher support for the smoking ban.

Hopotheses 1-6 in the context of prior research on the determinants of support for *localised* smoking bans

It is important to note here that, while national workplace smoking bans are a relatively new phenomenon, localized smoking bans are not. My searches revealed self interest and justice were also the explanatory frameworks investigated as determinants of support at the organisational smoking ban level. Greenberg (1994), for example, found evidence for an effect of both justice and self-interest on acceptance of workplace smoking bans; and Sheldon, Sinclair and Tetrick (1995) have noted that justice perceptions of organizational policies, including smoking bans, have important implications for employer-employee relationships. Similar to studies of AAP support, studies of local workplace smoking bans permit greater control over factors such as the ban's implementation process, and interpersonal factors to do with the ban's implementation. Consequently, whereas the impact of justice on organizational smoking ban support (and AAP support) has been studied across distributive, procedural and interactional justice subcomponents (e.g. Cropanzano et al. 2004; Colquitt, 2001), my hypotheses focus on distributive justice considerations as determinants of ban support. My self-interest hypotheses, however, were similar in nature to hypotheses made about smoking bans at the organizational level.

<u>Hypotheses based on expected group differences</u>

In addition to the six relational hypotheses described, I expect that self-interest also has implications for subgroup differences in support and standing on related constructs. More specifically, self interest theory implies group difference hypotheses, whereby groups expecting negative consequences should show lower support for the ban. Evidence in support of these group difference hypotheses will complement decisions regarding the appropriateness of my theoretical model in figure 1. <u>Hypothesis 7</u> is that relative to smokers, non-smokers will have a stronger belief in the dangers of environmental tobacco smoke, stronger beliefs in the rights of

workers and patrons to a smoke-free work environment, expect lower negative economic consequences, anticipate less personal difficulty in their jobs due to the legislation, and show greater overall support for the ban. Similarly, Hypothesis 8 is that owners who are managers, relative to non-owner managers, will have a weaker belief in the dangers of environmental tobacco smoke, weaker beliefs in the rights of workers and patrons to a smoke-free environment, a stronger belief in the negative economic implications of the ban, expect their jobs to become more difficult, and show lower overall support for the ban. That is, I anticipate that bar owners and smokers will have greater personal and group stake than workers and non-smokers, that they will anticipate more severe outcomes due to the ban, and hence express lower support for the legislation, and display lower endorsement of statements assessing important determinants of legislative support.

Prior to assessing support for these mean level hypotheses, I will demonstrate measurement and structural invariance across the sample subgroups (Drasgow, 1984; Millsap. 1995). Measurement invariance is required to permit interpretation of mean differences as quantitative change on the construct under study, rather than a study artifact due to either a difference in the domain being assessed by the measurement instrument across groups, or differences in subjective metrics of groups, or differing item intercepts. Showing relational equivalence for these groups will provide evidence that the determinants of support are the same across sample subpopulations of bar owners and bar workers and smokers and non-smokers. This information will be important to social marketers wondering whether media campaigns engendering support need to be targeted at segments of the population, or whether the same messages are likely to be effective for all sub-populations.

Summary of cross sectional hypotheses: a model of determinants of smoking ban support

To summarize, I have used two theoretical lenses to formulate a model of the determinants of support for the national smoking ban in New Zealand (shown in Figure 1). On the basis of theories of justice and self interest, I identified the most relevant constructs in the causal chain to support, and formulated six structural hypotheses. I also identified two group difference hypotheses based on self interest. There is a bountiful basis for using self interest and justice theories to study support for national smoking bans. This comes from the research using these theories to explain attitudes in other controversial settings (for AAP, see Bobocel, Son-Hing, Davey, Stanley and Zanna, 1998; for Politics, see Sears & Funk, 1990), as well as their use in the study of support for localised work smoking bans (e.g. Greenberg, 1994; Sheldon, Sinclair and Tetrick, 1995). My use of multiple theoretical frameworks for explaining human reasoning is routine in the social sciences. In recent times, multiple theory explanations have been reflected in dual processing theories (see Kahneman, Slovic, & Tversky [1984] for an example in decision making contexts). In applied settings, Chan, Schmitt, Jennings, Clause, and Delbridge (1998), and Schmitt, Oswald, Kim, Gillespie and Ramsay (2005) have shown self interest and justice frameworks to be complementary in understanding participant views on the fairness of college admission procedures and job selection procedures respectively. Based on these results, I expect these two theoretical frameworks to be complementary, rather than rival frameworks in aiding understanding of the determinants of support for the anti-smoking legislation. However, I make one final cross sectional hypothesis here. Sears and Funk (1990) showed that by and large, other than under exceptional circumstances, self interest has a moderate effect on support for policies and political candidates. On the other hand, in the AAP domain, justice has consistently been proven to explain reasoned human behaviour well (Harrison, Kravitz, Mayer, Leslie & Lev-

Arey, 1991). As a result, Hypothesis 9 is that justice constructs will have stronger relations with

support than self interest constructs.
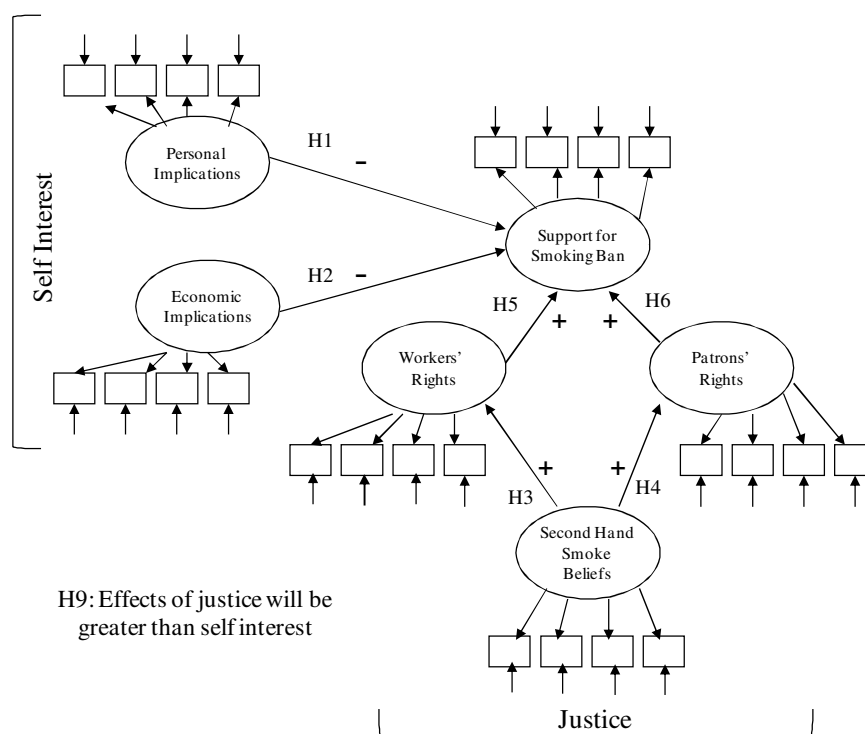
Figure 1. Hypothesized model of support for the national smoking ban

Hypotheses about change on constructs in my theoretical model over time

More often than not, studies of smoking ban support have been either prospective

examinations of whether people support a proposed ban (e.g. Galaif, Sussman, & Bundek, 1996;

Zullino, Besson, Favrat, Krenz, Zimmermann, Schnyder, Borgeat, 2003; Hammar, 2004; Klein,

Forster, McFadden, Outley, 2007), or snapshots of support for bans that are already in place (e.g.

Torabi & Seo, 2004; Martinez-Donate, Hofstetter, Gonzalez-Perez, Adams & Kotay, 2007).

Providing indications of the levels of support at a given point in time, in this way, is undoubtedly

useful. It helps identify the scope of the work public health advocates and educationalists have

ahead of them to engender support for smoking bans, and it can help to see whether politicians have the public support to implement bans in the first place. However, to confidently implement national smoking bans without fear of stakeholder backlash, policy makers need to know what happens to support for smoking bans within these stakeholder groups over time. Yet, my searches for longitudinal studies of smoking ban attitudes revealed them to be few and far between. The studies that do exist, while providing preliminary indications as to what I can expect to happen over time regarding the constructs in my cross sectional model, share many of the importunate methodological characteristics of studies already reviewed, undermining indubitable interpretations of research findings. Further specific pitfalls researchers must be cognizant of in relation to the analysis of change are comprehensively explicated by Chan (1998). Principal among them, in the case of the longitudinal smoking ban studies just cited, is that all of the longitudinal studies I located were based on just two time points. Yet, multi-wave designs (using three or more time-points) are essential if one to assess whether, for example, the change is reversible over the course of the study, or to assess the adequacy of different functional forms of growth, for example, to compare the fit of linear against non-linear change trajectories (e.g., quadratic or cubic trajectories) with latent growth modeling. Consequently, I will investigate change on the focal constructs of this study using 3-wave data, collected one month prior to the ban's implementation, and six and twelve months later, and use latent growth modeling. The simplest latent growth model is in fact a highly restrictive confirmatory factor analysis model, where the first, representing the initial status, has all loadings set to one. The second factor reflects the rate of change, and has factor loadings set to represent different forms of growth. A linear trajectory, for example, is represented by loadings of 1, 2, and 3, if three time-points are equidistant. I describe these models in more detail in chapter four.

Previous 2-wave analysis studies have indicated that support for smoking bans in restaurants and hospitals generally increases over time (Kaplan, Busner, Rogers, Wassermann, 1990), even amongst smokers (Trinidad, Gilpin, Pierce, 2005). Hence, Hypothesis 10 is that growth models will show support for the legislation increases over time. In another two wave study, Sciacca (1996) found that restaurant staff reported enforcing a localized restaurant ban to be easier than they expected 15 months later. Consequently, Hypothesis 11 is that I anticipate bar managers beliefs about how difficult enforcing legislation is for them to decrease over time. Overseas evidence unequivocally demonstrates that negative economic impacts are not experienced due to smoking bans (vide introduction). Hypothesis 12, therefore, is that beliefs that smoking bans negatively impact the industry will decrease over time, as bar managers come to realize there are no negative economic results due to the ban. On the other hand, beliefs about the dangers of ETS are more likely to be long held beliefs, built up over some years. Hypothesis 13 is that I do not expect any change in beliefs about the dangers of ETS over the course of this study, nor in beliefs about workers' and patrons' rights to smoke free environments. I have no reason to expect that the hypothesized changes will reverse or slow down during the year in which data collection was carried out, hence I hypothesize linear approximations will provide adequate fit.

If patrons can smoke in violation of the ban, without repercussion, it is extremely unlikely that a national smoking ban can achieve it aims of improving public health. It is of the utmost importance, therefore, that bar owners and bar managers take action to enforce the ban where it is violated. Moreover, the reason that I have proposed studying support for the national smoking ban in New Zealand is because I anticipate attitudes (i.e. support) will be closely tied to subsequent bar manager enforcement behaviour. I will, therefore, model these longitudinal

growth processes for constructs in my cross sectional models multivariately, with an outcome measure of enforcement behavior. Hypothesis 14, then, is that both the initial level of support for the national ban amongst bar managers, and the rate at which that support increases will be positively related to subsequent enforcement behaviour.

Chan (1998) suggested that a comprehensive approach to the analysis of change must be able to investigate whether there are groups of individuals that followed different developmental paths, and Muthen, Khoo, Francis and Boscardin (2002) noted that researchers have applied various post-hoc clustering techniques to identify groups for this purpose. We will use growth mixture modeling with categorical latent variables (Muthen & Shedden, 1999; Muthen, 2004) to examine whether there are subgroups of bar managers whose support for the legislation changes at different rates. Analytically speaking, this will enable us to infer from the data subpopulations that change at different rates. From a substantive perspective, it will increase certainty in the expected development of support for smoking bans in other countries. For example, policy makers could assess demographic similarities between their countries' populations, and the most similar subpopulation trajectory from this research, should subgroup heterogeneity be shown to exist, to identify the most likely developmental path smoking ban support would take. Growth mixture modeling is an exploratory technique and, as such, I do not form hypotheses at this juncture regarding the existence of subgroup trajectories.

Summary of research hypotheses

Contained in my 14 research hypotheses are crucial research questions that politicians, social marketers, and health educationalists need answered to enable them to decide whether, and how, to implement a national smoking ban in the United States. These hypotheses relate to three

key areas. First, hypotheses 1 to 6, and hypothesis 9, address the determinants of support for national smoking bans amongst this key stakeholder group. Next, hypotheses 7 and 8 examine group difference hypotheses implied by self interest theory. The final set of hypotheses addresses change over time. Hypotheses 10 to 13 examine change on the constructs from my cross-sectional model, how support itself, evolves over time, prior to, and post implementation of such a ban. And hypothesis 14 addresses the key question of how support for national smoking bans relates to enforcement behaviour during the year since the bans implementation. Growth mixture modeling will then be used to identify whether change in support is unitary in nature, or whether it follows multiple paths. By answering these questions more rigorously than previous research efforts, I hope to contribute momentum to the debate on a national smoking ban in other countries, and highlight ways in which support for bans might be engendered.

<u>Chapter three – testing the theoretical model of the nomology of support</u>

In this first study, I examine cross-sectional hypotheses (Hypotheses 1 to 9) outlined in my introduction. To summarise, hypotheses 1 to 6 are focused on confirming my theoretical model of support for the national smoking ban presented in Figure 1. I will present evidence from my examination of whether this model holds prior to the ban's implementation, as well as six months after, and one year later. Specifically, I am confirming the role of constructs implicated by self interest (beliefs about the negative economic implications of smoking bans and beliefs about how difficult smoking bans make bar manager jobs) and constructs implicated by justice theories (ETS beliefs and beliefs about patrons' and workers' rights to a smoke free work environment) in determining support for the smoke free legislation in New Zealand. I am also interested in seeing whether it is the self interest or justice related constructs have the stronger relationship with support for the legislation amongst bar managers and bar workers (Hypothesis 9), and in establishing support for my group difference hypotheses based on self interest for smokers and non-smokers, and bar owners and bar workers (Hypothesis 7 and 8).

<u>Sampling design and participants</u>

My sampling frame was a register of <u>all alcohol-licensed venues</u> approximately 3000 in New Zealand in October 2004. I assigned a random number without replacement between 1 and 3000 to each of the venues in my frame, ordered the list by the random numbers, and selected establishments numbered one through to 900 as my sample list. Data were collected by telephone interview. When the venues were then contacted, the duty manager was requested. The duty manager contacted was therefore effectively random. If a duty manager was not available, two call back attempts were made. If a duty manager was not available after these

three contact attempts, the venue was eliminated from the study – although the venue was not

replaced by adding another to the sample list. When a duty manager was contacted, the duty

manager was asked if they were also the venue owner, but no preference was given to owner-

managers or workers-managers. From this point, I will therefore use the term 'owner' to refer to

a participant that was a duty manager and an owner of the venue, and the term 'worker' to refer

to a duty manager that did not own the venue they worked in. If the contacted owner or worker

decided not to participate, they were thanked for their time, and the next venue on the list was

contacted. If the owner or worker did agree to participate, they were informed that they had been

contacted on behalf of the New Zealand Ministry of Health and the New Zealand Health

Sponsorship Council as part of a longitudinal study of the impact of bar manager attitudes to the

smoke free legislation. Participants were informed that participation was entirely voluntary,

responses would remain anonymous, and they were offered a summary letter of the overall

research findings if they chose to participate, and the opportunity to go into the draw for $150

worth of compact disc vouchers. At the end of each initial interview, the owner or worker that

had agreed to participate was asked if they would like to take part again in six months time.

Only participants who agreed to being contacted at the end of their first telephone interview were

contacted at times 2. Similarly, only those owners and workers who agreed to being contacted at

time 2 were contacted again at time 3.

Time 1 sample characteristics (1-month prior to ban)

Of the 900 bars and restaurants on my list, 705 were eligible to participate (i.e., still in

business at the time of the survey), and 535 agreed to participate, a response rate of 76%. The

reasons for non response were that a duty manager could not be contacted (n=103), that people

were too busy (n=42), people contacted were not interested (n=7), the survey was incomplete

(n=6), or the person disagreed with the legislation (n=3) or the person refused for some other reason (n=9). Out of the 535 completed interviews, 516 agreed to be re-contacted at time 2. At time 1, therefore, the main reason for non-response was due to problems contacting the venue. At Time One, the mean age was 40.37 years (standard deviation 12.08 years); 302 (56%) were male; 410 (77%) indicated European ethnicity, 64 (12%) indicated Maori ethnicity, with the remaining participants indicating another ethnicity or refusing; 293 (55%) were non-smokers; and 209 (39%) indicated they owned the venue they worked in.

Time 2 sample characteristics (six months after the ban)

Contacting the consenting time one participants at time two resulted in 346 completed interviews, a response rate of 67% on time 1 responses. The reasons for non-response at this second stage were that the bar manager no-longer worked at the venue (n=102), the venue no longer existed (n=15), the person was too busy (n=12), the contact was no longer interested (n=15), refusal for other reasons but not anti-legislation (n=3), and the time 1 person was un-contactable despite call backs (n=23). The likelihood of sample bias due to systematic attrition is low, because by far the primary reason for non-participation at time two was not being able to contact the time 1 participant. This is further reinforced when it is considered that the all of the non-responses at time 2 had agreed to be contacted again regarding this survey. Demographic characteristics of the sample at time two were very similar to sample characteristics at time one. At time two, the mean age was 42.47 years (standard deviation 11.87 years); 196 (57%) were male; 274 (79%) indicated Caucasian ethnicity, 35 (10%) indicated Maori ethnicity, with remaining participants indicating other ethnicity or refusing; 200 (58%) were non-smokers; and 151 (44%) indicating they owned the venue they worked in. Out of the 346 bar managers re-contacted, all but 1 agreed to be re-contacted at time 3.

Time 3 sample characteristics (12 months after the ban)

Contacting participants who took part at times one and two at time three resulted in 255 completed interviews, a response rate of 74% on time 2 responses. The reasons for non-participation at time 3 were staff no longer working at the venue (n=54), the venue no longer existed (n=6); the contact was too busy (n=9); the contact was not interested (n=2); the contact opposed the legislation (n=1); or refusal for other reasons (n=2); unavailable (n=10), or the questionnaire was incomplete in some way (n=6). Hence, the main reason for attrition at time 3 was not being able to get in touch with the bar owner or bar worker. This result, again, when coupled with the fact that re-contact attempts were all consensual, bolsters confidence that the non-response was not due to any self-selection bias. Demographic characteristics of the sample at time three were very similar to sample characteristics at times one and two. At time three, the mean age was 43.74 years (standard deviation 12.44 years); 148 (58%) were male; 204 (80%) indicated Caucasian ethnicity, 26 (10%) indicated Maori ethnicity, with remaining participants indicating other ethnicity or refusing; 150 (59%) were non-smokers; and 104 (41%) indicated they owned the venue they worked in

Measures

My searches of the literature did not reveal any suitable (i.e. reasonably brief scales with psychometric evidence of reliability and validity) psychometric scales assessing the constructs involved in my cross sectional model, so I needed to write my own. I initially wrote between 6 and 10 items for each construct in the study. These items were then qualitatively reviewed by colleagues to ensure they agreed the items could be accurately sorted into their appropriate constructs with complete agreement. This revision process resulted in five items per scale for

which there was complete agreement. Because my items had only, until this point, been tested using qualitative methods, I also examined item characteristics on half of the Time 1 sample, and deleted the worst performing item from each measure based on exploratory factor analyses and item total correlations. Hence, 4-item scales were used to test all hypotheses in the study. Item content for the Smoking Ban Questionnaire and classical test theory scale statistics for all resulting 4-item attitudinal measures are presented in Tables 1 and 2, respectively. Inter-scale correlations are presented in table 3. Item order was rotated during data collection to minimize the possibility of the order of item presentation influencing results. Items with (R) indicate items were reversed for purposes of calculating reliability, although this was unnecessary for structural equation modelling analyses which were conducted at the item level.

Bar manager support assesses support for the legislation using four 5-point Likert-type items, ranging from 1 (strongly disagree) to 5 (strongly agree). High scores indicate stronger support for the legislation. Internal consistency reliability was .88 at Time 1, .91 at Time 2, and .91 at Time 3.

Environmental tobacco smoke (ETS) beliefs assesses bar managers' beliefs about the dangers of ETS using four 5-point Likert-type items, ranging from 1 (strongly disagree) to 5 (strongly agree). High scores indicate the belief that ETS is a serious health threat. Internal consistency reliability was .82 at Time 1, .88 at Time 2, and .85 at Time 3.

Workers' rights assesses bar managers' views about the fairness of exposing hospitality industry workers to ETS using four 5-point Likert-type items, ranging from 1 (strongly disagree) to 5 (strongly agree). High scores indicate strong belief that exposing hospitality workers to ETS is wrong. Internal consistency reliability was .83 at Time 1, .84 at Time 2, and .82 at Time 3.

Patrons' rights assesses bar managers' views about the fairness of exposing patrons to ETS with four 5-point Likert-type items, ranging from 1 (strongly disagree) to 5 (strongly agree). High scores indicate stronger belief that exposing patrons to ETS is wrong. Internal consistency reliability was .76 at Time 1, .83 at Time 2, and .83 at Time 3.

Personal implications assesses bar managers' views about the extent to which the new smoking ban will make their job more difficult using four 5-point Likert-type items, ranging from 1 (strongly disagree) to 5 (strongly agree). High scores indicate that bar managers expect their jobs to be made more difficult by the legislation. Internal consistency reliability was .80 at Time 1, .82 at Time 2, and .81 at Time 3.

Expected economic impact assesses bar managers' expectations about the likely economic impact of the legislation using four 5-point Likert-type items, ranging from 1 (strongly disagree) to 5 (strongly agree). Higher scores indicate an expectation that the legislation will lead to negative economic consequences. Internal consistency reliability was .85 at Time 1, .89 at Time 2, and .92 at Time 3.

Table 1. Item sets used in research

Support Items
I fully support the Smoke free law
Smoke free law is a positive step for the New Zealand hospitality industry
Smoke free bars and pubs are a good idea regardless of the law
I oppose the idea of Smoke free bars and pubs ®
Beliefs about Second Hand Smoke Items
Breathing other peoples tobacco smoke can shorten a life
Even short periods of exposure to second-hand smoke can be harmful for a non-smoker
Second-hand smoke is a genuine health risk
The dangers of second-hand smoke have been exaggerated ®
Workers' Rights Items
Workers in pubs and bars have the right to work in an environment free of second-hand smoke
Workers should not be exposed to the risks of second-hand smoke
Employers should be required to provide a Smoke free work environment for their employees
If workers are worried about second-hand smoke they should change jobs ®
Patrons' Rights Items
Smoking patrons have no right to expose non-smoking patrons to second-hand smoke
Smokers have a right to smoke when drinking in bars and pubs ®
If people want a Smoke free environment they should not go to bars or pubs ®
The Smoke free law is unfair to patrons who smoke ®
Personal Implications Items
I am confident that patrons will respond positively when I ask them to smoke outside ®
I do not mind having to ask patrons to go outside to smoke ®
Having to ask people to go outside to smoke makes my job a lot harder
I expect a lot of resistance from smoking patrons when I ask them to smoke outside
Economic Impact
Bans on smoking in bars and pubs has no effect on patron numbers ®
Smoke free bars and pubs mean a decrease in overall patron numbers
Bans on smoking in bars and pubs does not affect the overall profits of these venues
Smoke free law has a negative impact on overall profits of bars and pubs

Table 2. Classical item statistics for the current study

Scale Statistics	N	Minimum	Maximum	Mean	Std Dev	Alpha
Support 1	535	4	20	12.12	5.04	.88
Second Hand Smoke Beliefs 1	535	4	20	14.55	3.46	.82
Workers' Rights 1	535	4	20	13.21	4.06	.83
Patrons' Rights 1	535	4	20	11.09	3.82	.76
Personal Implications 1	535	4	20	14.30	4.09	.80
Economic Impact 1	535	4	20	14.81	3.81	.85
Support 2	346	4	20	13.00	5.12	.91
Second Hand Smoke Beliefs 2	346	4	20	14.43	3.64	.88
Workers' Rights 2	346	4	20	13.85	3.99	.84
Patrons' Rights 2	346	4	20	12.24	4.12	.83
Personal Implications 2	346	4	20	10.85	4.25	.82
Economic Impact 2	346	4	20	13.87	4.68	.89
Support 3	255	4	20	13.48	5.10	.91
Second Hand Smoke Beliefs 3	255	4	20	14.47	3.38	.85
Workers' Rights 3	255	4	20	13.89	3.98	.82
Patrons' Rights 3	255	4	20	12.37	4.24	.83
Personal Implications 3	255	4	20	10.25	3.98	.81
Economic Impact 3	255	4	20	14.22	4.79	.92

Table 3. Scale inter-correlations for each of the three waves of the study

SCALE	SUPPORT1	ETS1	WR1	PR1	PIMP1	ECON1
SUPPORT1	1.00	-	-	-	-	-
ETS1	.64	1.00	-	-	-	-
WR1	.73	.58	1.00	-	-	-
PR1	.79	.60	.74	1.00	-	-
PIMP1	-.63	-.45	-.54	-.61	1.00	-
ECON1	-.66	-.48	-.56	-.63	.62	1.00
SUPPORT2	1.00	-	-	-	-	-
SHSB2	.66	1.00	-	-	-	-
WR2	.80	.67	1.00	-	-	-
PR2	.84	.63	.79	1.00	-	-
ETS2	-.72	-.48	-.59	-.59	1.00	-
ECON2	-.71	-.44	-.59	-.67	.57	1.00
SUPPORT3	1.00	-	-	-	-	-
ETS3	.71	1.00	-	-	-	-
WR3	.80	.66	1.00	-	-	-
PR3	.80	.67	.76	1.00	-	-
PIMP3	-.69	-.55	-.54	-.63	1.00	-
ECON3	-.67	-.49	-.50	-.64	.57	1.00

<u>Analyses</u>

I used structural equation modeling (SEM) to test hypothesized linkages using my entire Time 1 sample, and replicated the model at Times 2 and 3 (appendix 1. syntax e.g. 1 and 2). These analyses were carried out using the Mplus v4.2 computer program. All models were estimated using maximum likelihood estimation with item level covariance matrices, using the two step procedure advocated by Anderson and Gerbing (1988). While asymptotic distribution free estimation methods (also known as weighted least squares, or WLS, in LISREL and MPlus) are available to take into account the discretized nature of Likert scale data, such estimation methods require very large sample sizes, and in cases where sample size is moderate (as in the current study), their use is not advised (Jöreskog & Sörbom, 1996; Flora & Curran, 2004).

<u>Assessing the adequacy of my models</u>

Goodness of fit in structural equation models is evaluated in part by an overall test of χ^2. The model is rejected if χ^2 is significant. However, the typical form of statistical hypothesis testing is often inappropriate to judge the model discrepancy in structural equation models. Here, a significant χ^2 may reflect a poorly specified model, or the high power of the test, or failure to satisfy other requirements of the test (vide Marsh, Hau & Grayson, 2005). The result is that even trivially misspecified and theoretically appropriate models will be rejected if the sample size is sufficiently large, and even poorly specified models may be accepted if the sample size is small enough. Researchers have thus listened to the views, of among others, Cudeck & Browne (1983) and McDonald & Marsh (1990). These authors contended that structural models are approximations of reality that are unlikely to be able to be strictly proved true or false, and a number of other fit indices have been proposed. In this paper, therefore, for all models, I also

present values of the following fit indices: the Comparative Fit Index (CFI: Bentler, 1990); the

Non-Normed Fit Index (NNFI: Bentler & Bonnet, 1980; also known as the Tucker-Lewis

Index); the Root Mean Square Error of Approximation (RMSEA: Steiger, 1990), and the

Standardized Root Mean Square Residual (Jöreskog & Sörbom, 1988). The CFI and NNFI

range from zero to 1, and conventionally, values over .90 are considered to indicate good fit (Hu

& Bentler, 1998); for RMSEA values below .10 indicate a good fit, values below .05 indicate

very good fit (Steiger, 1990), and for SRMR, values below .06 indicate good fit (Hu & Bentler,

1998). Nested χ^2 comparisons were used for comparing nested models. Information criteria

(Akaike's Information Criterion: AIC; and the Bayesian Information Criterion, BIC) were used

for comparing non-nested models. The lower information criterion value indicates the better

fitting model (see Byrne, 1998). In sum, to judge the fit of my models, I relied on several

assessment criteria, beginning from the position that all models are approximations that would be

rejected given sufficient sample size. Considering multiple fit criteria provided converging

evidence from multiple sources regarding the fit of my structural equation models.

Measurement and relational equivalence analyses

Before drawing conclusions regarding mean differences between sample subpopulations

(smoker/non-smoker and owner-managers/worker-managers; see Hypotheses 7 and 8 above) , I

had to demonstrate that scales functioned similarly across subpopulations with measurement

equivalence analyses (i.e., scales needed to be bias free). This shows that the measurement

instruments are functioning similarly for all populations. Measurement equivalence holds when

individuals with equal standing on a construct, but sampled from different subpopulations, have

the same expected scores when groups are on a common metric (e.g., Drasgow, 1984, 1987;

Steenkamp & Baumgartner, 1998). At present, establishing measurement invariance can be done

with two classes of methods, those based on item response theory (IRT) and those based on

confirmatory factor analysis (CFA). For a detailed discussion of these approaches, see Raju,

Laffitte, and Byrne (2002). Because IRT-based analyses require larger sample sizes than were

available to me, a procedure based on mean and covariance structures analysis (MACS; Sörbom,

1974) was chosen for this investigation. In recent times, a degree of consensus has emerged with

regard to the order of these tests. My MACS analyses followed what was recommended by

Vandenberg and Lance (2000) and Vandenberg (2002) (appendix 1. syntax e.g. 3). I first tested

the overall equality of covariance matrices. I next tested for invariance of factor loading and

intercepts sequentially.   In short, this procedure started with a free baseline model, where item

parameters are free to vary except for factor reference items for each construct whose loading is

set to 1 to identify the metric, and whose intercepts were constrained to be equal across groups.

The latent mean for each of the six constructs in the focal group was then freely estimated,

whereas the latent mean for the reference group is set to zero. I followed this baseline model

invariance tests with metric and scalar equivalence analyses, and then an examination of the

equivalence of error covariances. When I had identified the most appropriate measurement

model, I conducted single degree of freedom chi-square tests of the mean differences to

investigate the group difference hypotheses (H7 and H8). Non-significant differences were fixed

at zero prior to estimating the invariance of structural paths in my model across bar manager

subgroups (Smoker/Non-smoker and Owner-Manager/Worker-Manager). If these paths are

equivalent across groups, relational equivalence is said to exist. More specifically, relational (or

predictive) equivalence holds when individuals with the same expected score on the predictor

construct have the same expected score on the criterion construct (Drasgow, 1984; 1987). Only

if relational invariance holds could I be confident that the same causal mechanisms underlie

support for workers and owners and smokers and non-smokers alike.

Results of cross sectional analyses

At Time 1, results for my measurement model were as follows: χ^2=627.43, df = 237,

RMSEA=.06, CFI=.95, NNFI=.94, RMSEA=.06, and SRMR=.047. All of these statistics

indicate a well-fitting measurement model (e.g. Byrne, 1998), and that I can proceed with

structural modelling. Moreover, this measurement model showed better fit than a competing

single factor measurement model based on non-nested model comparisons using information

criteria AIC and BIC. For these comparisons, the lower AIC and BIC indicate the better fitting

model. The AIC and BIC for the hypothesized model were 35038.29 and 35410.85 respectively,

compared with 35990.090 and 36298.41 for the single factor model. This indicates that the six

factor measurement model I hypothesized fits better than the competing single factor model.

Other fit statistics for the single factor measurement comparison model were as follows: χ^2 =

1609.623, df = 252, CFI=.81, NNFI=.80, RMSEA=.10, and SRMR=.07. Results for my

hypothesized structural model also indicated good fit. Fit statistics were χ^2= 825.76, df=243,

CFI=.92, NNFI=.91, RMSEA=.07, and SRMR=.06. All of these values are suggestive of a well

fitting model (e.g. Byrne, 1998). Residuals were also distributed symmetrically about zero, and

there were no large standard errors with all structural parameters significant at least p<.05.

Importantly, at Time 2, my proposed model was replicated, and similar fit indices were observed. Results for the measurement model at time 2 were as follows (χ^2= 567.94, df=237, CFI=.95, NNFI=.94, RMSEA=.06, and SRMR=.05), which again fitted better than the single factor model based on AIC (22700.34 versus 22109.49) and BIC (22977.28 versus 24421.056). Other fit statistics for the single factor comparison model were as follows: χ^2 = 1418.80, df = 252, CFI=.81, NNFI=.78, RMSEA=.12, and SRMR=.07. Results for my structural model at time two were χ^2 = 809.95, df=243, CFI=.91, NNFI=.89, RMSEA=.08, and SRMR=.07. Again, residuals were also distributed symmetrically about zero, and there were no large standard errors with all structural parameters significant at least p<.05.
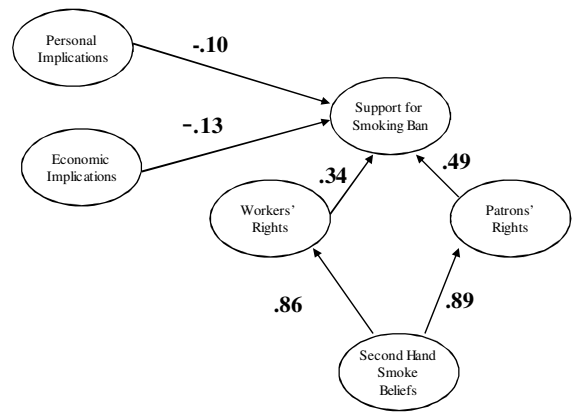
Time 1 results n=535 $x2$= 825.76, DF=243 RMSEA=.07 SRMR=.06 CFI=.92, NNFI=.91

Figure 2. Cross sectional standardized time one results
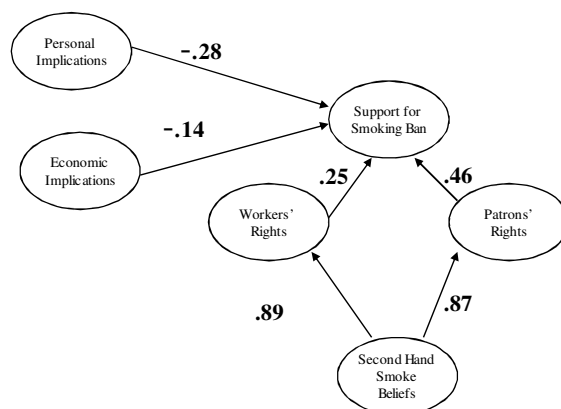
Time 2 results n=346 $x2$= 809.95, DF=243 RMSEA=.08 SRMR=.07 CFI=.91, NNFI=.89

Figure 3. Cross-sectional standardized time two results

Similarly, the cross sectional model fitted well at time 3. Results for the measurement model at time 3 were as follows (χ^2= 498.65, df=243, CFI=.94, NNFI=.93, RMSEA=.07, and SRMR=.06), which again fitted better than the single factor model based on AIC (16280.60 versus 16954.14) and BIC (16588.65 versus 17209.11). Other results for my single factor comparison model were as follows: χ^2 = 1202.23, df=252, CFI=.78, NNFI=.76, RMSEA=.12, SRMR=.07). Results for my structural model at time 3 were χ^2 = 583.24, df=243, CFI=.92, NNFI=.91, RMSEA=.07, SRMR=.05). Parameters again were well estimated (all significant at least at p<.05), and residuals were symmetrically distributed about zero. Results of these measurement and structural models for times 1 to 3 are presented in table 4, and figures 2-4. Having established that my hypothesized models fit well, we can proceed with examining support for my specific hypotheses from the size and direction of structural parameter estimates.
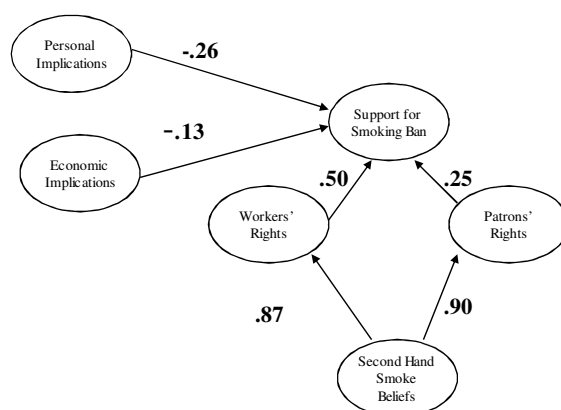
Time 3 results n=255 $x2$= 583.24, DF=243 RMSEA=.07 SRMR=.05 CFI=.92, NNFI=.91

<u>Figure 4.</u> Cross-sectional standardized time three results

<u>Table 4.</u> Cross sectional structural equation model results

Cross-sectional model results							
	Chi-square	df	p	CFI	TLI	RMSEA	SRMR
Measurement models							
Time 1	627.43	237	<.01	0.95	0.94	0.06	0.05
Time 2	567.94	237	<.01	0.95	0.94	0.06	0.05
Time 3	498.65	237	<.01	0.94	0.93	0.07	0.05
Structural models							
Time 1	825.76	243	<.01	0.92	0.91	0.07	0.06
Time 2	809.95	243	<.01	0.91	0.89	0.08	0.07
Time 3	583.24	243	<.01	0.92	0.91	0.07	0.05

First I show that the model parameters are largely invariant over time, as shown in

multiple group modeling where time is the grouping variable. Technically speaking, this violates

independence requirements for multiple group analyses, yet I include it because it is often done.

Results of this analysis in Table 5 show that the model fit is strong even when relational

invariance constraints are added to metric and scalar invariance. Supporting these results is the

fact that very similar magnitudes for parameter estimates were observed at Times 1, 2 and 3,

indicating that observed relations were largely unaffected by time. For example, the biggest

difference between Time 1 (Figure 2) and Time 2 (Figure 3) is that the Personal Implications to

Bar Manager Support path increased in absolute magnitude from -.10 to -.28. If this is due to

sampling fluctuation, and the true value for this path coefficient lies in the middle of this range,

my conclusion that justice factors are stronger determinants of bar manager support than

rational/economic factors remains unaffected. This interpretation is also supported by the

analysis of the structural parameters of my model over time using a single group model, testing

relationships one relationship at a time. This indicated the parameters were largely invariant

over time (appendix 1. syntax e.g. 4). These results indicate my initial model provides

acceptable estimates of the links within my nomology of bar manager support for the smoke free

legislation. Given that the proposed model was replicated at Times 2 and 3 with parameter

estimates of the same signs and similar magnitudes, there were no negative error variances or

large standard errors, residuals were relatively evenly dispersed, and models at all time points

showed good fit using conventionally accepted goodness of fit indices, I concluded that

relational hypotheses were supported. Despite this, given the violation of independence due to

multiple group modeling, my preference is to focus on discussion of the structural parameter

estimates from single group analyses, which I turn to now.

Invariance over three periods	x^2	df	Model Comparison	Δx^2	Δdf	p	CFI	TLI	RMSEA	SRMR
Model 1: Configural Invariance (baseline) Identification constraints only (referent loading for each factor set to one across groups, intercepts of referent constrained equal across time, covariances among factors freely estimated (i.e. no structural paths estimated).	1694.021	711					.94	.94	.06	.05
Model 2: Metric Invariance* Model M1 with loadings constrained equal across time	1778.571	747	M1 vs M2	84.55	36	.00	.94	.94	.06	.06
Model 3: Scalar Invariance Model M2 with intercepts constrained equal across time	1992.792	783	M3 vs M2	214.22	36	.00	.93	.93	.06	.07
Model 4: Error Invariance Model M3 with error variances constrained across time	2177.220	831	M4 vs M3	184.43	48	.00	.92	.92	.07	.07
Model 5: Structural model added to M3 Model M3 with structural paths estimated separately across time	2298.112	765	M5 vs M3	519.54	18	.00	.91	.91	.07	.07
Model 6: Relational invariance Model M4 with structural paths estimated separately across time	2321.930	777	M6 vs M5	23.82	12	.02	.91	.91	.07	.07

Table 5. Results of measurement invariance across time

More specifically, Hypothesis 1, which posited that if bar managers believed that the legislation would make their jobs more difficult, they would report lower levels of support, was supported, with negative path estimates between these constructs at all time points (-.13 at Time 1 and -.28, at Time 2, and -.26 at time 3). Hypothesis 2, which hypothesized that bar managers would report lower levels of support for the legislation if they believed that it would have negative economic implications for their industry, was also supported. The path coefficients between these constructs were estimated at -.13 at Time 1, -.14 at Time 2, and -.14 at Time 3. Justice related structural hypotheses were also supported. Hypothesis 5, that believing that environmental tobacco smoke is a real danger would positively predict beliefs about fairness of exposing workers' and patrons' to environmental tobacco smoke was supported. This is shown by the positive path coefficients at Time 1 (Figure 2) between environmental tobacco smoke beliefs and both workers' rights (.86) and patrons' rights (.89). Similar values were observed at Time 2, with these paths estimated at .89 and .87 respectively, and at Time 3, with these paths estimated at .87 and .90 respectively. Believing that workers and patrons have a right to a smoke-free work environment positively predicted personal support for the legislation, providing support for Hypothesis 6. The path from workers' rights to support was .33 and the path from patrons' rights to support was .49. At Time 2 these paths were estimated at .25 and .46 respectively, and at Time 3, .50 and .21 respectively.

While all hypothesized paths were of the predicted sign, the strongest determinants of smoking ban support were clearly the justice-related constructs. This can be seen in Figure 2, for example. Here the path estimates from both personal implications and economic implications to bar manager support (-.10 and -.13 respectively) are considerably lower than the path estimates from my justice constructs to bar manager support for the legislation (.34 for workers' rights and

.49 for patrons' rights). Wald chi-square tests from cross sectional models of the hypothesis that the effects of the justice component of the model on support were equal to the effects of the self interest component of the model on support were rejected at all three time points, supporting Hypothesis 9, that that justice constructs have the greatest impact on support.

Comparisons of owner vs. bar workers and smokers vs. nonsmokers

The results of analyses examining the measurement and structural equivalence of bar owner and bar worker subgroups are presented in tables 6 and 7. Table 6 shows that measurement and scalar invariance are supported, based on the non-significant increases in χ^2 between the models with only identification constraints and the models where loading and intercept constraints are imposed. Table 6 also shows that error variance equivalence was rejected. Based on comments by Chan (1998) suggesting equality of error covariances is only likely to hold in contrived situations, I relaxed the error variance constraint prior to estimating the significance of latent mean differences across smoker and non-smoker groups for each of the six constructs under study. These mean difference tests indicated that workers expressed higher support for the legislation than owners (.44); expressed a higher belief in the rights of workers' to a smoke free work environment (.30); expressed a higher belief in patrons' to a smoke free work environment (.24); expressed higher beliefs in the dangers of ETS (.27); had lower beliefs about the personal implications of enforcing the legislation (-.08); and lower beliefs about the negative economic implications of the legislation (-.19). Yet, the only significant differences were for support and workers' rights. Thus, Hypothesis 7 is only partially supported. Subsequently imposing relational equivalence on the structural parameters of this model showed the structural equivalence holds. This can be seen from the non-significant increase in

between the model where structural parameters are freely estimated across groups and the model

where structural parameters are constrained equal across owner-worker groups.

Table 6. Equivalence results for owner workers

Owner Worker Comparisons	χ^2	df	Model Comparison	$\Delta \chi^2$	Δ_{df}	p	CFI	TLI	RMSEA	SRMR
Model 1: Configural Invariance (baseline) Identification constraints only (referent loading for each factor set to one across groups, intercepts of referent constrained equal across groups, covariances among factors freely estimated (i.e. no structural paths estimated).	964.112	474					.93	.92	.062	0.05
Model 2: Metric Invariance Model M1 with loadings constrained equal across owners and workers	982.573	492	M1 vs M2	18.46	18	.43	.93	.93	.06	.06
Model 3: Scalar Invariance* Model M2 with intercepts constrained equal across owners and workers	1016.628	510	M3 vs M2	34.06	18	.01	.93	.93	.06	.06
Model 4: Error Invariance Model M3 with error variances constrained across owners and workers	1078.779	534	M4 vs M3	62.15	24	.00	.93	.92	.07	.07
Model 5: Structural model added Model M3 with structural paths estimated separately across groups	1225.072	524	M5 vs M3	208.44	14	.00	.91	.91	.07	.07
Model 6: Relational invariance Model M4 with structural paths estimated separately across groups	1231.854	530	M6 vs M5	6.78	6	.34	.91	.90	.07	.07

*The scalar invariance model was my adopted measurement model

Table 7. Mean difference test results for owners and workers

		Owner Worker Comparison (Relative to Owners)					
		Support	Workers' Rights	Patrons' Rights	Second Hand Smoke Beliefs	Personal Implications	Economic Implications
Model 1	χ^2	1016.63	1016.63	1016.63	1016.63	1016.63	1016.63
	df	510	510	510	510	510	510
Model 2	χ^2	1028.04	1032.27	1024.27	1023.83	1017.33	1022.21
	df	511	511	511	511	511	511
	$\Delta \chi^2$	11.41	15.64	7.64	7.21	.70	5.59
	Δ_{df}	1	1	1	1	1	1
	Mean Difference	.44	.30	.24	.27	-.08	-.19
	p	.00	.00	.01	.01	.40	.02

Results for measurement equivalence across smoker and non-smoker groups and owner

and worker groups are presented in Tables 8 and 9. Scalar invariance was supported for

owner/worker subpopulations, as indicated by the non-significant χ^2 increases presented in table

8 due to the addition of the loading and intercept invariance constraints. Addition of error variance constraints resulted in a significant increase in χ^2. Again, based on Chan's (1998) comments, I relaxed the error variance constraint prior to estimating the significance of latent mean differences across smoker and non-smoker groups for each of the six constructs under study.

In table 9, it can be seen that smokers expressed significantly lower support for the legislation (-.85); expressed significantly lower belief in workers' rights to a smoke free work environment (-.35); expressed significantly lower belief in patrons' rights to a smoke free environment (-.36); expressed significantly lower belief in the dangers of ETS(-.46); anticipated significantly higher personal implications due to enforcing the ban (.36), expressed and significantly higher beliefs about the negative economic consequences of the ban (.34). Thus, my group difference hypothesis in relation to worker non-workers, Hypothesis 8, was supported. Relational equivalence was also supported for these subpopulations. This can be seen in table 6 from the non-significant increase in   between the model where the structural paths are freely estimated across groups (Model 5) and the model where these structural paths are constrained equal across groups (Model 6).

Table 8. Equivalence results for smokers and non-smokers

Smoker Non-Smoker Comparisons	χ^2	df	Model Comparison	$\Delta \chi^2$	Δ df	p	CFI	TLI	RMSEA	SRMR
Model 1: Configural Invariance (baseline) Identification constraints only (referent loading for each factor set to one across groups, intercepts of referent constrained equal across groups, covariances among factors freely estimated (i.e. no structural paths estimated).	928.538	474					.94	.93	.06	.05
Model 2: Metric Invariance Model M1 with loadings constrained equal across owners and workers	963.240	492	M1 vs M2	34.70	18	.01	.93	.93	.06	.06
Model 3: Scalar Invariance* Model M2 with intercepts constrained equal across owners and workers	991.213	510	M3 vs M2	27.97	18	.06	.93	.93	.06	.06
Model 4: Error Invariance Model M3 with error variances constrained across owners and workers	1042.054	534	M4 vs M3	50.84	24	.00	.93	.93	.06	.06
Model 5: Structural model added Model M3 with structural paths estimated separately across groups	1192.092	522	M5 vs M3	150.04	12	.00	.91	.90	.07	.07
Model 6: Relational invariance Model M4 with structural paths estimated separately across groups	1199.394	528	M6 vs M5	7.30	6	.29	.91	.90	.07	.07

*The scalar invariance model was my adopted measurement model

Table 9. Mean difference test results for smokers and non-smokers

		Non-smoker Smoker Comparisons (Relative to Non-Smokers)					
		Support	Workers' Rights	Patrons' Rights	Second Hand Smoke Beliefs	Personal Implications	Economic Implications
Model 1	χ^2	991.21	991.21	991.21	991.21	991.21	991.21
	df	510	510	510	510	510	510
Model 2	χ^2	1037.38	1014.10	1009.99	1013.68	1009.07	1011.69
	df	511	511	511	511	511	511
	Δ df	1	1	1	1	1	1
	$\Delta \chi^2$	46.16	22.89	18.78	22.47	17.86	20.48
	Mean Difference	-.85	-.35	-.36	-.46	.36	.34
	p	.00	.00	.00	.00	.00	.00

<u>Summary</u>

To summarize, based on the results of my structural equation modeling, I observed strong support for my cross sectional hypotheses. Over three measurement occasions, the relationship between personal implications and support was -.10, -.28, and -,26; between economic implications, the values were -.13, -.14, and -.13; between ETS beliefs and workers' rights, the values were .86, .89, and .87; between ETS and patrons rights, the values were .89, .87 and .90. Finally, the workers' rights to support paths were .34, .25, and .50, and the patrons' rights' to support paths were estimated at .49, .46 and .25. The hypothesized model, therefore, appears to provide a parsimonious and accurate picture of the nomology of bar worker support for the national smoking ban in New Zealand. These results show that constructs expected to determine support for national smoking bans amongst bar managers on the basis of self interest, namely, beliefs about the negative implications of the legislation, and beliefs about the difficulty of enforcement, were indeed negatively related to bar managers' support levels. Moreover, constructs expected to predict bar managers support on the basis of theories of justice, namely ETS beliefs, was positively related to support. This relationship, also as expected, was mediated by beliefs in the rights of patrons and workers to an environment free of tobacco smoke. Expected patterns of group differences, implied by self interest theory, also supported my theoretical model. However, there is more to support than these analyses reveal. Specifically, each of the constructs in my cross sectional models is likely to be dynamic, and can more accurately be described as a processes. To elucidate further the nature of support for smoking bans, it is critical that these constructs are modeled as processes, using longitudinal data analysis methods, and with distal outcomes to show the impact of attitudes on behaviour. This is the focus of the next chapter of this dissertation.

Chapter four – modeling support for smoking ban over time

To this point, I have outlined reasons why two theoretical paradigms for explaining reasoned human behaviour, <u>self interest</u> and <u>justice</u>, might be expected to explain support for the smoke-free legislation amongst a sample of bar owners and bar workers, and I have demonstrated that justice concerns appeared to be in the forefront of people's their minds when deciding on their levels of support for the national smoking ban. These relations held across subpopulations of owners and workers and smokers and non-smokers. Yet these two wave analyses elucidate little about the nature change in support over time – for example, do the causes of support increase over time? Does support itself increase? Are these changes linear (e.g. do they reverse)? How does initial status and rate of change relate to important outcomes, such as the degree of enforcement behaviour in response to instances of ban violation? The primary focus of this section of the paper, therefore, is to model the change in support for the national smoking ban, with its causes and outcomes, longitudinally, using multi-wave data (3 time-points). Specifically, this study is intended to assess support for <u>hypotheses 10-14</u>.

<u>Method</u>

<u>Sampling design and participants</u>

The sampling design was the same as that described in my cross sectional analyses in section one. Similarly, the demographic characteristics of the sample at times 1, 2 and 3 were described in detail in study one.

<u>Measures</u> The six measures from my cross sectional analyses were also used in this study, and their development id described in study 1. In this section, however, I use multiple indicator latent growth models based on the <u>three</u> strongest loading items across time (i.e. a

count was made of the number of times an item loaded in the top 3 items over the 3 time periods in my exploratory cross sectional analyses, and the item with the lowest count was removed from the scale). Additionally, three new measures were introduced in this section of the study, enforcement behaviour, smoking status, and whether or not the participant reported experiencing respiratory related health problems.

Enforcement behaviour was a two part question, which was asked at times two and three. Bar managers were first asked if they had seen patrons smoking in violation of the ban. Those responding yes were then asked what action was taken in response (1= no action, 2= action taken if time permitted, 3 = immediate action was taken). Scores for the measures at times two and three were summed to give an overall enforcement behaviour score. Bar managers who reported not seeing smokers at either time point had their enforcement behaviour score recorded as missing data.

Health problems and smoking status were coded as dichotomous single item indicators, 1 indicating smoker for smoking status, and 0 indicating non-smoker; 1 indicating respiratory related health problems (e.g. coronary related problems, asthma) for health status and 0 indicating no health problems.

Analyses

The constructs identified in my cross sectional models were analyzed with latent growth models. According to Muthen & Khoo (1998) and Chan (1998), the simplest latent growth model can be viewed as a restrictive confirmatory factor analysis model that has two factors with repeated measures of the construct over three or more time as indicators (three or more time points are required for model identification). The first latent factor is the intercept of the growth

process, and has the loadings of the repeated measures set at one. The second factor defines the slope of the curve, and represents the shape of the curve over time. The means of these intercept and growth factors represent the group growth parameters, and are overall measures of the intercept and slope for all subjects on the model. The variance of the latent factors reflects the variation of each individual subject around the overall growth parameters – hence the growth model is considered a random coefficients model. For a technical description of latent growth modeling, and its advantages over other more conventional forms of analysis, the reader is referred to Meredith & Tissak (1984, 1990), McCardle & Epstein (1987), Muthen (1991), Muthen & Khoo (1998)and Willet & Sayer (1994). For an excellent non-technical introduction and tutorial, readers should refer to Chan (1998). I extended this model to a 2nd order model where the estimated time scores are latent variables. While a non-saturated quadratic acceleration factor model cannot be estimated with just three time points due to identification constraints, unspecified non-linearity can be tested by freeing the final time score rather than fixing it at 2. This appropriateness of this can be evaluated with a single degree of freedom chi-square test because the models are nested.

The growth framework I have used is considered is a single level model, and hence I do not talk about within and between variables in subsequent discussion. In latent variable growth modeling, time is captured by fixing the factor loadings to represent time. Conversely, in multilevel models, time is captured as a vector of data. The mean and variance of between level dependent variables correspond to the mean and variance of the factors for the initial status, and rate of change in the multivariate approach I have taken. SEM is more flexible in that it enabled me to use latent variable measurement, and it was easier to extend to include distal outcomes

related to the initial status and growth parameters. Individually varying times of observation, which multilevel growth deals well with, were not present in my research.

For all unconditional growth models (i.e. growth models where there is no predictor), the mean of the initial status factor was set at zero and the variance of the intercept, mean of the slope, and variance of the slope are freely estimated (appendix 1. syntax e.g. 5). My Likert scale data met recommended normality requirements for maximum likelihood of skewness <2 and kurtosis <7 (West, Finch & Curran, 1995), hence all unconditional models used full information maximum likelihood (FIML) estimation. FIML analyzes incomplete data without imputation, making distributional assumptions about covariates critical to missing data handling, producing unbiased parameter estimates when data are missing completely at random (MAR), performing well when data are only missing at random (MAR), and performing better than listwise and pairwise deletion when missing data are non-ignorable (Little & Rubin, 1989; Schaefer, 1997; Muthén, Kaplan & Hollis, 1987). All models had MACS constraints on loadings and intercepts to demonstrate that the change modeled is alpha change (i.e. not beta or gamma, c.f. Golembiewski, Billingsley, and Yeager, 1976; Sörbom, 1974; Chan, 1998; Millsap & Hartog, 1998; Vandenberg & Lance, 2000). The range of the enforcement indicator used in my distal outcome model, however, suggested treating it as a categorical variable would be more appropriate. For my final longitudinal modeling involving the enforcement behaviour variable, therefore, I used the M-Plus WLS-MV estimator. In contrast to WLS/ADF, WLS-MV has been shown to perform well in samples where n= 250 (Muthén, du Toit, & Spisic, 1997). WLSMV uses listwise deletion for cases with missing data on predictor variables, because there is currently no capability for missing on predictor variables when data are categorical in Mplus. Hence, for WLS modeling, n=255 (appendix 1. syntax e.g. 6).

<u>Longitudinal results</u>

Muthen & Khoo (1998) state that the key modeling results for the basic linear growth model are (1) estimates of the average initial status, (2) the average growth rate, and estimates of the variation across individuals of (3) initial status, and (4) growth rate. All models showed reasonable fit by traditionally accepted standards (Hu & Bentler, 1998; 1999). Table 9 summarises the fit statistics for these models, table 10 summarises the key parameters for unconditional (no predictor) growth models, and table 11 summarises the mean differences over the three time points for each process.

<u>Table 10.</u> Unconditional growth models for 6 processes in cross-sectional model

	Unconditional Growth Model Results							Non-linearity check		
Model	Chi-square	df	p	CFI	TLI	RMSEA	SRMR	Chi-square	df	p
Support*	42.466	34	.151	.996	.996	.022	.034	41.319	33	.284
Economic Implications*	85.155	34	.000	.972	.971	.053	.064	81.286	33	.049
Personal Implications**	213.830	34	.000	.875	.868	.099	.103	NA	NA	NA
Worker Rights	51.553	32	.021	.989	.988	.032	.040	51.319	31	.629
Patron Rights***	92.453	33	.000	.962	.958	.058	.054	83.676	32	.003
ETS beliefs	57.992	33	.005	.985	.984	.038	.053	NA	NA	NA

*non-significant negative residual of slope fixed at zero. N/A means model would not converge when final time score was freed.

<u>Table 11.</u> Unconditional growth model key modeling parameters

	Intercept				Slope				Covariance	
Model	Mu	std error	Sigma^2	std error	Mu	std error	Sigma^2	std error	Covariance	std error
Support	.000	.000	1.591*	.166	.225*	.036	.169*	.043	-.039	.074
Economic Implications	.000	.000	.429*	.084	-.055	.031	.133*	.030	.068	.045
Personal Implications	.000	.000	.856*	.124	-.408*	.036	.12*	.038	-.020	.062
Worker Rights	.000	.000	.576*	.086	.099*	.026	.025	.042	.019	.048
Patron Rights	.000	.000	.310*	.050	.153*	.020	.035	.022	.007	.025
ETS beliefs	.000	.000	.536*	.073	.013	.024	0.08*	.033	-.074	.039

*significant at p<.05.

Table 12. Estimated time scores for three time points for each process

Model	T1	T2	T3
Support	.000	.225	.450
Economic Implications	.000	-.055	-.109
Personal Implications	.000	-.408	-.816
Worker Rights	.000	.099	.197
Patron Rights	.000	.153	.306
ETS beliefs	.000	.013	.027

Changes in support for the national smoking ban over three waves

The results for the fit of unconditional multiple indicator latent growth model of support for the national smoking ban is presented graphically in figure 5. This Support growth model shows support for the legislation increased linearly at each time period, from zero to .225 at time two, and from .225 to .450 standardized units at time three. The mean of the slope factor for the three time period model was significantly different from zero, indicating that the observed change was significant. Showing what happens to support for the legislation to politicians was a leading objective of this study. Here I have shown conclusively, using an improved methodology on previous studies and in a national level context not before investigated, that support increases substantially and significantly over time. The variance of the intercept and slope growth factors was also significant, indicating that there was significant variation in, respectively, starting levels of support amongst bar managers, and in the rate of change in support across bar managers. The relation between the intercept and the slope was negative but non-significant. The single degree of freedom non-linearity test was non-significant, indicating that a non-linear approximation of the change could not describe the model significantly better than the linear model. Thus, my first longitudinal hypothesis, hypothesis 8, was supported.
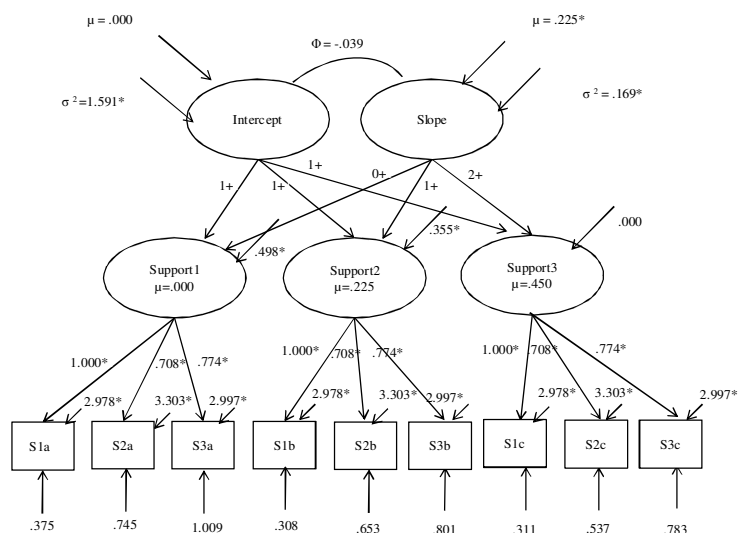
Figure 5. Standardized estimates for unconditional growth model for support

Changes on self interest related constructs over three waves

Hypothesis 9, which specified that bar managers beliefs about how difficult the legislation was to enforce would decrease over time, was supported. These beliefs decreased significantly, as evidenced by the significant slope mean of -.408, from .00 at Time 1 to -.408 at time 2, and to -.816 at time 3. The intercept variance and slope variance were also both significant, indicating significant variation in initial beliefs of how difficult smoking legislation was to enforce, and in the rate of change in these beliefs across individuals. My final longitudinal hypothesis from the self interest component of my model, hypothesis 10, that beliefs about the negative economic implications of the ban would decrease, however, was not supported. While the significant variance for the intercept indicated that there was significant variation in the starting levels of beliefs about the negative economic implications of national smoking bans, the non-significant slope for this process indicates the mean change was not significantly different from zero. These results are illustrated graphically in figures 6 & 7.

Figure 6. Standardized estimates for unconditional growth model for economic implications

Figure 7. Standardized estimates for unconditional growth model for personal implications

Figure 8. Standardized estimates for unconditional growth model for ETS

Changes on justice related constructs over three waves

Moving to results of the longitudinal justice component of my model, hypothesis 11, that

these mean levels on these constructs would remain stable, was partially supported. Beliefs

about the dangers of ETS remained stable, as evidenced by the non-significant mean for the

slope of this growth process. There was, however, significant variation in the initial status on

beliefs about the dangers of ETS, as shown by the significance of the intercept factor for this

process in table 9. On the other hand, in contrast to hypotheses 11, rights based beliefs about

workers' and patrons' entitlements to smoke free environments both increased significantly, as

shown by the significant means for these growth processes (.099 for workers' rights and .153 for

patrons' rights). There was also significant variation in both the initial status and rates of change

for these processes, as shown by the significant variances for the intercept and slope factors of

both growth processes. For patrons' rights, there was also some evidence of non-linearity in the

increase, as evidenced by the significant improvement of fit due to freeing the final time score. This was the only process for which a non-linear model more adequately characterized change.
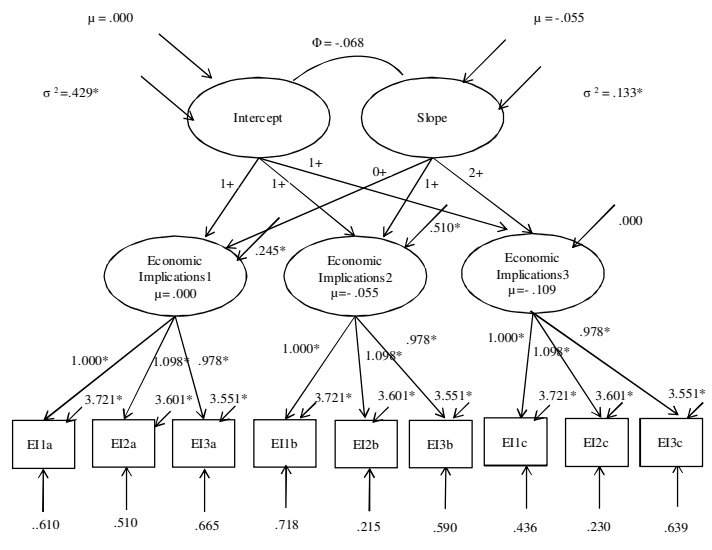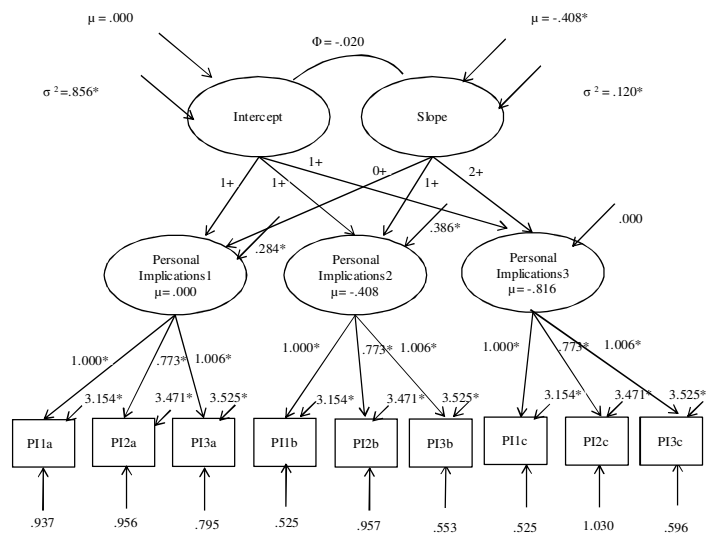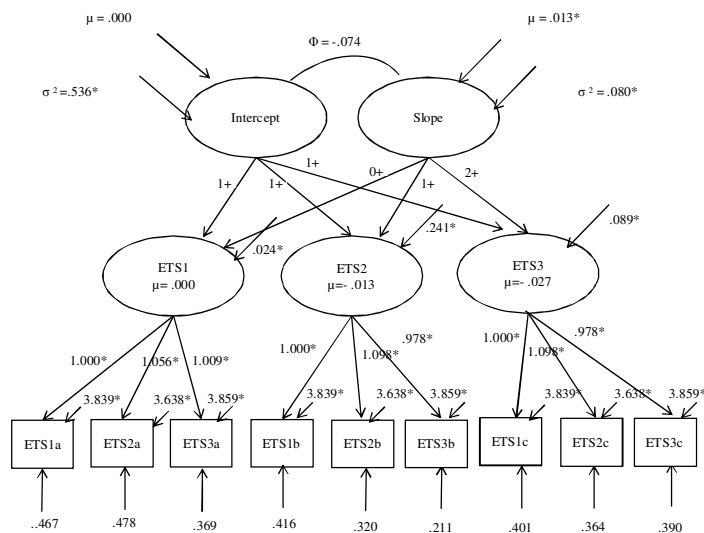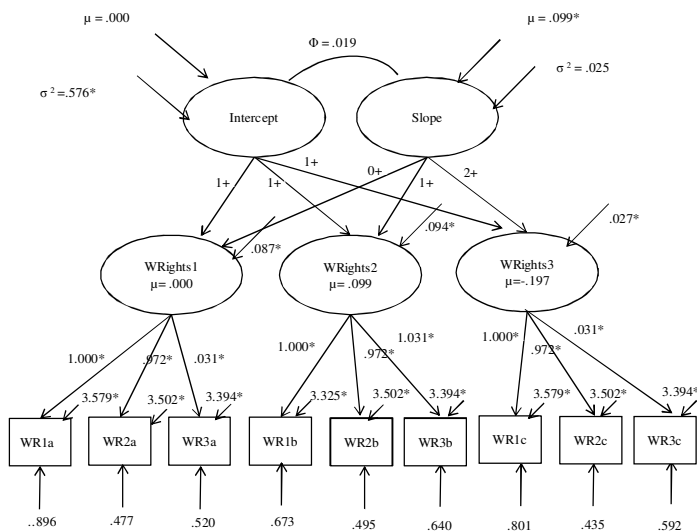

Figure 9. Standardized estimates for unconditional growth model for workers' rights
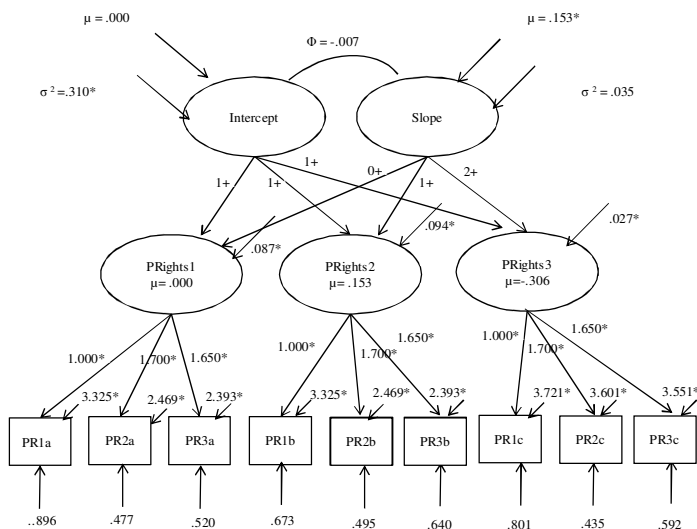
Figure 10. Standardized estimates for unconditional growth model for patrons' rights

<u>Enforcement as a critical distal outcome variable</u>

Support for the national smoking ban was chosen because it is an attitude that I anticipated would be linked to subsequent bar manager <u>enforcement behaviour</u>. Following achievement of satisfactory model fit for the single process growth models, therefore, I estimated several further models. Trying to model six parallel processes is an extremely ambitious model, and perhaps not unexpectedly, resulted in non-positive definite latent variable covariance matrices, even when allowing for correlated errors which can sometimes resolve this problem. The six processes could not be modeled together. I therefore needed a strategy to develop a parsimonious model that embedded the growth model of support (see figure 5) in the broader context of the theoretical framework outlined in chapter one, along with enforcement behavior as a distal outcome variable, and accounting for the influence on support of variables like smoking status and health status.

My strategy involved identifying the most significant predictor of support for the ban, statistically and practically, to model with support, as well as the enforcement behaviour outcome, and smoking status and health status. From cross-sectional modeling, Wald chi-square testing indicated that beliefs about the dangers of ETS was a significantly stronger predictor of support for the smoke free legislation that beliefs about the personal and economic implications of the ban. ETS was therefore the most relevant construct to model with support. Moreover, the latent growth model for ETS beliefs (Figure 8) indicated that the mean level for ETS did not change significantly over time (i.e. the slope was not significantly different from zero). When a construct does not change over time, but predicts a growth model intercept and rate of change, it is called a time invariant covariate. The growth model in such cases is then considered conditional, because support growth is conditioned on the predictor (in this case, growth in

support is conditioned on ETS). On the other hand, certain variables related to the support

growth process are expected to change over time. For example, smoking status changes as

people quit smoking. Respiratory related health problems might also be expected to change with

time. Such variables are known as time varying covariates. These are typically modeled as an

additional growth process, run in 'parallel', or as predictors of the factor scores at each time

period. The latter option was chosen here. For these reasons, I therefore estimated a conditional

growth model of support for the smoking ban ,where ETS beliefs is a predictor of the support

growth model intercept and slope. The model is a conditional model of support because support

is conditional on ETS beliefs. To link the support growth process to enforcement behaviour, I let

the initial status and rate of change growth factors predict the enforcement behaviour variable. I

included smoking status and health problems as time varying covariates, and included the

enforcement action bar managers reported being taken as distal outcomes of the latent growth

model random effects (figure 11). Fit statistics are presented in table 12. The chi-square p-value

for this model was non-significant, indicating that this model fits very well. Similarly, CFI and

TLI are near 1, RMSEA is under .05. With the WLSMV estimator, SRMR is not given, rather

the weighted mean root residual is provided, with values below .9 indicating good fit. My final

growth model of the antecedents and consequences of support for the legislation is therefore

presented in figure 11.

Table 13. Final model fit for embedded growth model with auxiliary information

	Conditional support growth model with distal outcomes							
	Chi-square	df	p	CFI	TLI	RMSEA	SRMR	WRMR
Final Model*	35.663	27	.123	.996	.996	.035	-	.826
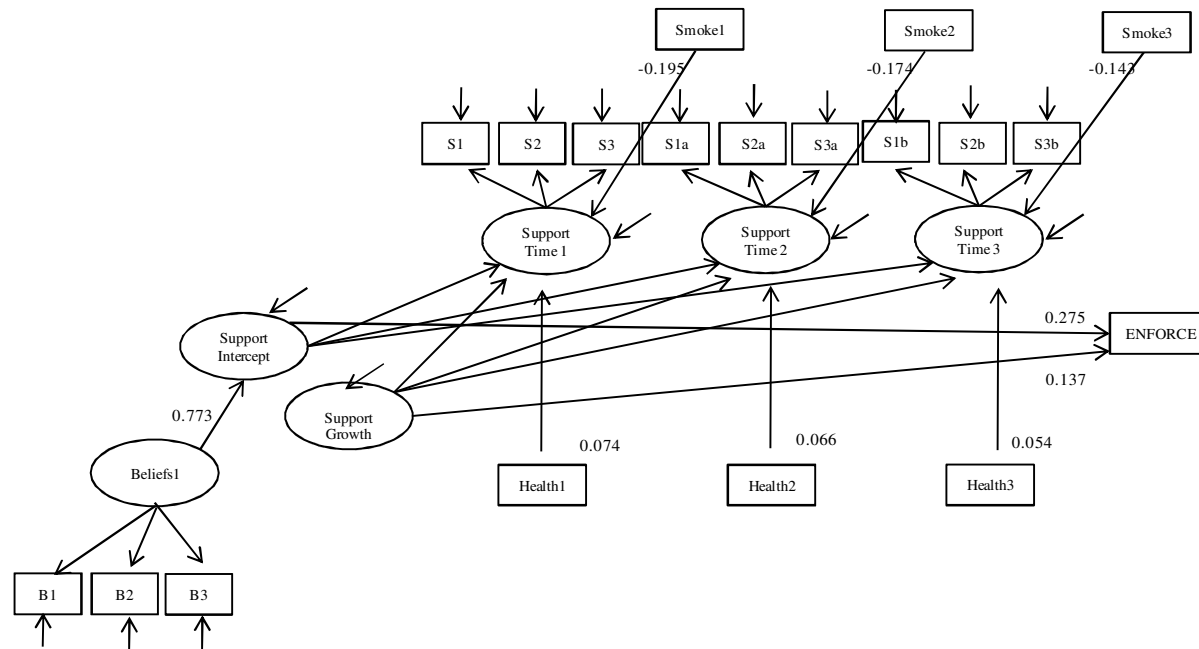
Figure 11. Embedded growth model of antecedents and consequences of support over time. Second order loadings set for linear growth, MACS constraints on loadings and intercepts. Paths to enforcement constrained equal. Model shows perfect fit, all parameters significant at p<.05. All estimates standardized.

Figure 11 shows that ETS beliefs are <u>significantly</u> related to the initial level of support for the smoke free legislation, but ETS beliefs do not significantly predict the rate at which support changes, so this is omitted. Similarly, owner status, whether the bar worker was also the bar owner) failed to significantly predict the growth factors, and was also omitted from the model. The means for the three time-scores (support at time 1 was - .123, support 2 was .310, and support 3 was .729) in the model showed that support increases linearly over the year in which the study was conducted. Note the first time score is not zero due to the inclusion of ETS as a predictor. Figure 11 also shows that at each of these three time periods, smoking status, a time varying covariate, is significantly and negatively related to support for the national smoking ban. Smokers show lower support for the ban at all 3 time periods, consistent with cross sectional results. In a similar fashion, the existence of respiratory related health problems at each of the three time points is significantly and positively related to support for the ban. Bar managers with health problems showed more support for the ban at all three time periods. Finally, the significant paths between the initial level of support (the intercept factor of the support growth process) and the change factor (the slope factor for the support growth process) show that bar managers' initial levels of support, and the rate at which that support increases, are significant predictors of the level of enforcement behaviour bar managers reported being taken in response to ban violations. Hence, <u>hypothesis 12</u> was supported. The size of these path coefficients, .275 for the intercept predicting enforcement, and .137 for the intercept predicting enforcement, are sizable for social sciences research. The model depicted in figure 11, therefore, provides a graphical representation of my answer to the three key research questions politicians need answered, which are embodied in my research hypotheses, and outlined in my introduction. First, it is primarily commonsense justice related constructs that determine support for the

national smoking legislation. Second, support for the national smoking legislation increased consistently over time. Finally, the initial level of support and the rate at which support changes significantly predict enforcement behaviour.

<u>Summary</u>

Longitudinal hypotheses were therefore largely supported. Support increased over time. Beliefs about the difficulty of enforcing the legislation declined over time. In contrast to my hypotheses, beliefs about the negative economic impact remained stable. My hypothesis that the justice component of the model would remain stable was partially supported. Beliefs about the dangers of environmental smoke remained unchanged. Beliefs about patrons' and workers' rights to a smoke-free environment, on the other hand, increased significantly. These views, it seems, are more malleable than I anticipated. Finally, I provided a parsimonious model of what happens to support over time. This model is represented graphically in figure 11. ETS beliefs significantly predicted the initial support, but not the rate at which support changes. The initial level of support and the rate at which support changes significantly predicted enforcement behavior in the year after the ban. The model also accounted sensibly for two time varying covariates, health status and smoking status.

Chapter five – exploring variation in growth rates of unobserved subgroup

In my final model in chapter four (Figure 11) I showed good fit for an embedded growth model of support for the smoke free legislation, where the growth model was predicted by ETS beliefs, and where growth itself predicted enforcement behaviour in the year since the ban. This model demonstrated that bar managers' support for the legislation increased linearly over the three time points in the study. It also demonstrates that the initial level of support, and the rate at which bar managers' support increases, is significantly related to the level of enforcement behaviour bar managers report taking in response to ban violations, in the year since the legislation came into effect. Moreover, time varying covariates of respiratory related health problems and smoking status influence support scores at each time period.

Knowing one year ahead of time what the causes of enforcement behaviour are, can be extremely useful information for politicians and social marketers. This means they can begin to educate people now to inform the attitudes that they know will predict enforcement behaviour in the one year. Yet, certain questions about the nature of the change observed remain unanswered. Chan (1998) suggested that any change assessment methodology should be able to ascertain whether the change is unitary or multipath. Yet this question cannot be answered by conventional single group growth modeling, because such models assume that individuals come from a single population with common parameters for means, slopes, intercepts and error variances (Muthen, 2004). In my growth model in Figure 11, for example, this constraint results in a single population mean for bar managers' initial status on support, which is fixed at zero. While there was significant variation in starting levels on support, this starting level variation centres around the single population intercept mean. Similarly, there was a single population mean for growth in support of .225. While there was variation in this growth rate across

individuals, as shown by the significant variance for the slope, again, this variation was centred about a single population slope mean. Several researchers have noted that this can be limiting (e.g. Muthen & Shedden, 1999; Muthen, 2004).

If any subgroup heterogeneity were observable, I could examine it with multiple group growth modeling. For example, observed heterogeneity in support trajectories for the national smoking legislation might be expected due to smoking status, or such differences in growth rates of smoking ban support might be due to the absence or presence of respiratory related health problems. However, in my model in Figure 11, recall that smoking and health status variables were introduced as time varying covariates, rather than as a time invariant covariate, or as an observed grouping variable in multiple group modeling. The choice of how to enter covariates into the model, directly (within model), or indirectly (multiple group approach) hinges on the nature of the effect I expect to observe. Using a multiple group approach allows the grouping variable the potential to modify every parameter in the model. Conversely, entering the variables as time invariant or time varying covariates allows the variable only to influence the mean trajectory of the change, while other model parameters remain unaffected. My cross sectional analyses had indicated measurement and structural equivalence for my model across smoker and non-smoker and bar owner and non-owner subgroups – indicating that these types of variables were unlikely to moderate structural relationships. Rather, they are likely to influence mean trajectories (consistent with cross sectional results in chapter one, where smoking status influenced mean levels, but did not moderate structural relationships). Accordingly, the effect of health and smoking status variables was modelled by bringing them into the model directly. Any remaining heterogeneity in support growth rates in my model, I believe, is more likely to be unobserved than observed.

However, unobserved heterogeneity cannot be modelled with tradition growth modeling. Recent work on growth mixture modeling by Muthen & Shedden (1999), however, relaxed the assumption that variations in initial status and growth parameters, captured by the random effects, describes variation in parameters is around a single population mean. Growth mixture modeling explores subgroup heterogeneity using latent trajectory classes, that is, categorical latent variables (Muthen, 2004). Examining unobserved heterogeneity in growth trajectories for bar manager support for the national smoking ban in New Zealand is the focus of this chapter.

Method

Sampling Design and Participants

The sampling design was the same as that described in my cross sectional analyses in section one. Similarly, the demographic characteristics of the sample at times 1, 2 and 3 were described in detail in study one.

Measures

All of the measures used in my growth modeling study in chapter three were also those included in my mixture models in the current analysis.

Analyses

Muthen (2004) has suggested that the appropriateness of the unconditional model for determining the number of classes has not been fully understood, and that the better answer to the number of classes in growth mixture modeling is provided by the model that includes antecedent and auxiliary information. Mplus technical support suggested one should first do the analysis without covariates as a practical matter, but then not be surprised if the class

enumeration comes out differently due to adding covariates. Consequently, I estimated the number of classes based on an unconditional growth mixture model (appendix 1. syntax e.g. 7), and then I extended the growth mixture model to include the ETS predictor, the time varying covariates of smoking status and health status, and the distal enforcement variable (appendix 1. syntax e.g. 8). Including auxiliary information in the sense of antecedents and consequences in this fashion leads to the notion of a general growth mixture model (Muthen, 2004). I present results of class enumeration from both forms of analyses. Mixture models were estimated using the default MLR estimator in Mplus. A well known problem in the estimation of mixture models is local optima. To avoid adopting a model based on a local solution, multiple start values must be used (Muthen, 2004). However, Hipp & Bauer (2007) pointed out that little is known about the extent to which the likelihood surface must be probed through varying start values to avoid local solutions. The default random starts strategy in Mplus involves generating 10 sets of random start values, running through 10 iterations for each set, taking the value with the highest loglikelihood, and continuing to iterate with that set until convergence criterion is satisfied. Hipp & Bauer suggested that for complex models, these defaults are insufficient, and that the start values must be varied considerably more, with between 50 and 100 starting values needed. As a precautionary measure, all mixture models were estimated with 500 starting values which were run for 50 iterations before selecting the set with the highest loglikelihood for further estimation.

Results

Table 14 reports the results of unconditional growth mixture models of support for one, two, three, and four classes. This table shows that the two class solution had a lower loglikelihood, lower AIC, and lower BIC than the two class solution, suggesting that the two class model was a better fit to the data than the single class solution. The entropy was also high

at .86, suggesting clear classification of bar managers into each of the two classes. The evidence for the two class solution is reinforced by the three significance tests provided by Mplus. For the Voung-Lo-Mendell-Rubin likelihood ratio test for 1 versus 2 classes, the Lo-Mendell-Rubin adjusted likelihood ratio test, and the bootstrapped likelihood ratio test, a small p-value indicates the K-1 class model ought to be rejected in favor of the K-Class model (Muthen & Muthen, 2006). The test statistics for these tests were all significant at p<.001, indicating the two class model should be preferred over the single class model. The asterisk next to the results for the three-class solution indicates a non-significant negative residual variance for the intercept factor of the growth model had to be fixed to zero for the model to converge. The Voung-Lo-Mendell-Rubin likelihood ratio test for 1 versus 2 classes, the Lo-Mendell-Rubin adjusted likelihood ratio test, and the bootstrapped likelihood ratio test for three versus the two class solution are therefore not presented. When comparing the two and three class models I am left with only information criteria on which to decide, as the models are no longer the same due to the negative residual variance for the intercept in the three class model being fixed at zero. While the AIC, BIC and SSAIC were lower for the three class model, Tofighi & Enders (2006) have suggested fixing variances at zero for model convergence probably indicates over extraction of classes.

When looking at the trajectories of the three class model compared to the two class model, it also showed that the additional class was a small class with a similar slope, although it had a lower intercept. The class added little theoretically to my understanding of the development in support, and because it probably indicated an over extraction of classes, I prefer the two class solution for the unconditional model. The mean trajectories for the two class growth mixture model are presented in figure 12. In this unconditional two class model, the first contained 49% of bar managers. The intercept for this class was significant, indicating

significant variation in the starting levels of support for this class, although the slope for this

class was not significantly different from zero. This indicates that this class was a high support

class that, on average, did not change over the course of the study.   On the other hand, the

second class, comprised of 51% of bar managers, was a class of bar managers that increased over

the course, with a significant slope mean of .45.

Table 14. Growth mixture model results for unconditional models

General growth mixture model	Log Likelihood	AIC	BIC	SSAIC	Entropy	p-value for VLMR-LRT	LMR - Adjusted likelihood ratio test	Paramteric bootstrapped likelihood ratio test
1 class model	-4994.511	10029.022	10114.667	10051.181	-	-	-	-
2 class model	-4915.814	9877.629	9976.121	9903.111	.86	<.001	<.001	<.001
3 class model*	-4868.868	9785.737	9888.511	9812.328	.89			
4 Class model*	-4811.299	9676.598	9792.219	9706.513	.99	.001	.001	<.001

* indicates a non-significant negative residual for the intercept of the growth process needed to be fixed at zero for

the model to converge.

Figure 12. Mean trajectories for two class unconditional growth mixture model

Next, I estimated a conditional model. This model was, apart from three modifications,

exactly the same as the model in Figure 11 from my previous analyses.   First, I let a latent class

variable capture unobserved subgroup variation in growth rates of support. Then, I regressed the

class variable on ETS beliefs, and regressed enforcement behaviour on the categorical latent

class variable. This created a multinomial logistic regression sub-model in the growth mixture

model where the latent class variable is regressed on the time invariant ETS beliefs construct. In

this model, I also show the impact of the latent class variable on the categorical distal outcome of

enforcement behaviour. In Mplus this is not accomplished via an on 'statement', rather it is

observed in mean differences on the outcome, in the case of continuous observed variables, or in

threshold differences, in the case of ordered categorical distal outcomes. The results for the one

through four class solutions for the general growth mixture model are presented in Table 15.

Table 15. Growth mixture model results for conditional models

General growth mixture model	Log Likelihood	AIC	BIC	SSAIC	Entropy	p-value for VLMR-LRT	LMR - Adjusted likelihood ratio test	Paramteric bootstrapped likelihood ratio test
1 class model	-7924.858	15943.717	16144.983	15995.79	-	-	-	-
2 class model	-4266.736	8617.472	8766.205	8633.055	.88	<.001	<.001	<.001
3 class model*	-4242.123	8582.245	8755.767	8600.425	.86			
4 Class model*	-4229.475	8570.949	8769.26	8591.727	.88	1.000	1.000	<.001

*parameters fixed to avoid singularities (where likelihood goes to infinity preventing convergence).

These results again show that the two class model is superior to the single class model, by

both information criteria and the Voung-Lo-Mendell-Rubin likelihood ratio test, the Lo-Mendell-

Rubin adjusted likelihood ratio test, and the bootstrapped likelihood ratio test. For the three and

four class models, parameters were required to be set at zero to avoid singularities in the

information matrix. Because of this, despite the lower loglikelihood and information criteria, I

prefer the two class model. Tofighi & Enders (2006) have suggested that requiring parameters to

be set at zero probably indicates over-extraction of classes.

For the selected two class model, the reference class comprised 41% of bar managers,

and was showed a significant negative slope of -.20, indicating this was a decreasing class. The

variance of the slope factor was also significant, indicating individual variation about the mean

rate of decline. There was also significant variation about the starting levels of support amongst this class. The second class was comprised of a group of bar managers whose mean level of support was higher at the beginning (higher intercept) than the reference class, and whose support increased over the year of the study, as shown by the significant slope mean of .53. The variances for the intercept and slope within this class were also significant. Examination of auxiliary information in the form of smoking rates and health problems amongst the bar managers within classes shows that the high starting and increasing class was characterized by a lower proportion of smokers than the decreasing support class, and was comprised of a higher proportion of bar mangers with respiratory related health problems than the low starting decreasing support class.
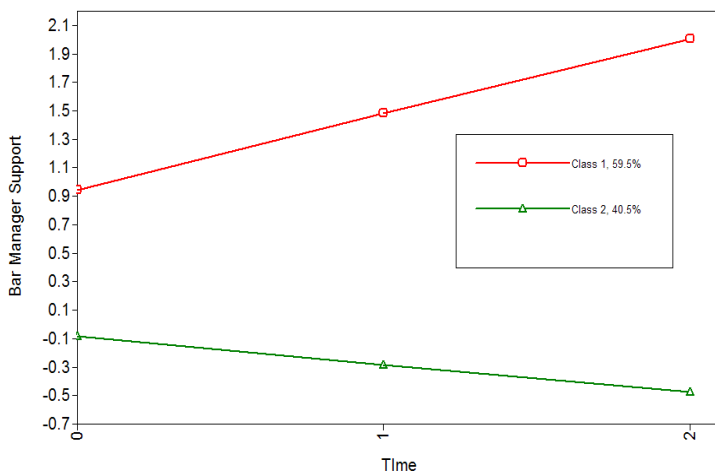
Figure 13. Mean trajectories for two class general growth mixture model

The positive and significant coefficient .94 for regression of the latent class variable on ETS indicates the increase in the log-odds of being in the high starting and increasing class relative to the low starting decreasing class when beliefs in the dangers of ETS is high. Taking the natural log of the coefficient shows the odds of being in the increasing class when ETS

beliefs are high are 2.57 times higher than when ETS is low. Examination of the thresholds for enforcement across latent classes shows that the thresholds at which bar managers probability of being in a lower category of enforcement behaviour shifts to a higher category of enforcement behaviour are lower for the increasing class than for the decreasing class. The difference in thresholds shows that class membership affects enforcement behaviour. Specifically, the increasing class reported taking more enforcement behaviour than the decreasing class. The composition of the classes with respect to auxiliary information is consistent with what one would intuitively expect, and from the perspective of interpretability, supports my adoption of the two class solution. The increasing support class was comprised of a lower proportion of non-smokers with higher instances of respiratory related health issues, and conversely, the decreasing class was characterized by a higher proportion of smokers with and lower reported respiratory related health issues.

Table 16. Auxiliary information summary for each class

	Support 1	Support 2	Support 3	Health 1	Health 2	Health 3	Smoke 1	Smoke 2	Smoke 3
Class One	0.94	1.48	2.01	0.33	0.33	0.3	0.35	0.31	0.33
Class Two	-0.08	-0.28	-0.48	0.55	0.53	0.54	0.2	0.18	0.22

Summary

In this chapter I identified two subclasses whose support took on different trajectories. The first was an increasing support class that took more enforcement behavior, and the second was a decreasing support class, who took less enforcement behavior. Table 16 shows that these two classes where characterized by intuitive standing on important auxiliary variables.
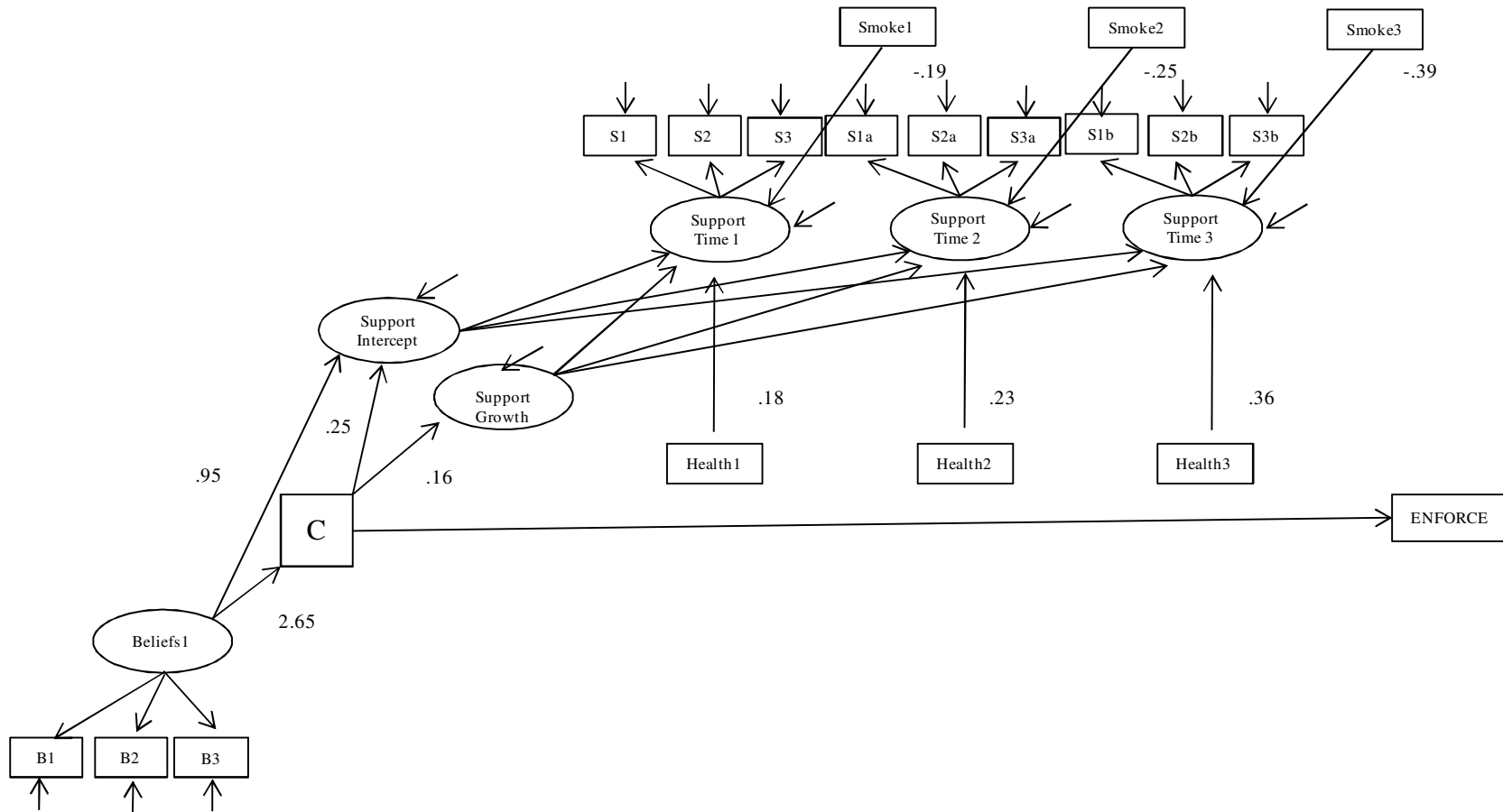
Figure 14. Final general growth mixture model of the nomology of support with two classes. Estimates are un-standardized.

Parameters equal across classes. The regression of enforcement on the categorical latent variable C is captured by differing class

thresholds for enforce, described in text. The value for the regression of the categorical latent variable C on beliefs is an odds ratio.

Chapter six - discussion and conclusions

In my view, there is little scope for debate regarding the necessity or the legitimacy of national smoking bans. The pernicious threat environmental tobacco smoke poses to public health means bans are required, and they cannot be argued against on the basis of economic arguments. These have consistently been shown to be empirically vacuous. Imposing national smoking bans to mitigate such a threat as that posed by environmental tobacco smoke is also consistent with conventional Libertarian principles. From another angle, one might also examine the legitimacy of bans from a standard biomedical ethics perspective (Beauchamp & Childress, 2001). This approach would way the merits of national bans against criteria of beneficence, non-malfeasance, and respect for autonomy. Even from this perspective, I again contend, smoking bans are warranted and just. The moral mandate clearly requires a national ban. Beneficence without malfeasance requires acting in the interest others with minimum harm. However, as I have shown, self interest constructs, autonomy aside, are neither impacted by smoking bans, nor material to people's expressions of ban support. Finally, I have argued that at times when the importance of individual rights are weighed against public health, one must weigh them in favor of doing others no harm, i.e., in favor of public health.

Yet, as things currently stand, the United States is not among the 145 countries that have ratified the 2003 World Health Organization Framework Convention on Tobacco Control (FCTC) calling for, among other measures, clean-air policies (Koh, Joossens, & Connolly (2007). I have argued that one of the reasons that such a ban has not been implemented by the United States, and one of the reason the United States has not ratified the FCTC, is that policy makers are uncertain as to whether their major stakeholders support a national ban, what influences stakeholders support for bans, and how this support will evolve over time. With

messages about smoking bans emanating from tobacco industry lobby groups that are not in accord with the extant research, I am not surprised. But politicians need accurate information on smoking ban support, because they have a short to medium term interest in keeping their stakeholders satisfied. While I am not so naïve as to believe that knowledge of the antecedents and consequences of support is the only factor determining whether such a ban eventuates, I firmly believe all policy makers interested in reelection have a vested interest in keeping their stakeholders satisfied. If a ban is to come about, therefore, sound research on how support for smoking bans evolves over time is in acute demand amongst politicians in the United States.

There is also a pressing need for information about the determinants of smoking ban support amongst public health educationalists and social marketers. It is widely accepted that isolation or framing effects can impact individual decision making. In the realm of taxation, for example, McCaffrey and Baron (2006) have found that 'people decide complex matters by responding to the most salient or obvious aspect of a choice set or decision problem. Following researchers such as Khaneman & Lovallo (1993) and Idon, Chugh, Bereby-Meyer, Moran, Grosskopf & Bazerman (2004) they suggested this 'framing' or 'isolation effect' was a meta-label for a variety of more discrete cognitive biases, including many under the heuristics banner from Khaneman, Slovic & Tversky (2004). In the realm of taxation, they found this framing effect resulted in, among other outcomes, individuals' reversing expressed preferences, and people being influenced by labels used in discussion of taxation. Campion and Chapman (2005) have suggested that this very effect is exploited by tobacco industry representatives working within the constraints of journalism.

And so, it is of critical importance that public health educationalists and social marketers have information on the aspects of smoking bans that are most susceptible to isolation and

framing effects. This will allow them to counter anti-smoking ban messages that are likely to emerge, should the United States implement a national smoking ban. If it is found that it is primarily self interest based concerns that determine support, such as how difficult it will make bar manager jobs, policy makers may be swayed to focus efforts on making enforcement easier, for example, taking a soft enforcement approach in the beginning. Under these circumstances, social marketers would also be wise to focus campaigns on overseas research that has shown that the difficulty of enforcing a ban was not as great as initially anticipated by bar and restaurant workers (e.g. Sciacca, 1996). If it is self-interest based on a perceived threat to their jobs due to an economic downturn, politicians may be convinced by knowledge that the negative economic impacts do not occur (vide introduction). On the other hand, if it is common sense justice based constructs that determine support, politicians may want to ignore the self interest angle all together aim to engender support for bans based on the notion that an individual's right to smoke cannot be entertained at the expense of the health of others. The purpose of this thesis has been to identify for politicians, public heath educationalists, and social marketers what the causes of support are, in order that they may use this information to facilitate the introduction of national smoking bans in their own countries. I have done so using theoretical and methodological advances from psychology to address problems with earlier studies that did not adequately resolve questions about smoking ban support.

Limitations of the current study

While I have applied theory and advanced statistical models to answer my research question, like all research, has limitations. It is important that I draw attention to these before discussing the implications of my findings. Principle among these is that these my research findings are based on self report responses to survey data. As a result, the size of the

relationships may be somewhat inflated by the common method variance (Feldman & Lynch, 1988). Also, other than bar managers and owners subpopulations could have been studied (e.g., customers and bar staff). I have also highlighted the likely transportability of my national level findings from New Zealand to the United States. Yet, it may be that there is a setting in which this study could have been conducted that is more germane to the United States, such as a state level study. Finally, due to the survey length limitations, I was unable to examine the effect of dimensional aspects of justice, and focused on notions of commonsense justice. In my discussion below I will discuss the importance of these other forms of justice and their implications for politicians and social marketers. All of my research findings are interpreted, accordingly, with these caveats in mind.

<u>Cross sectional findings: What are the determinants of support and what implications does this have for those wanting a ban in the United States?</u>

My cross sectional model showed good fit for my proposed theoretical model using structural equation modeling. In addition, constructs implicated by commonsense justice explained significantly more variation in support than constructs implicated by self interest theories. The focus on the negative economic bans by tobacco industry lobby may therefore be a red herring if convincing the public to support smoking bans in a principle aim of politicians, health educationalists, and social marketers. Believing that the bans make bar manager jobs more difficult and that bans lead to industry downturns are only modestly related to support for national smoking bans, in both an absolute sense, and in relation to the explanatory power of common sense justice variables. In addition to good model fit at the overall sample level, my model was further reinforced by expected patterns of subgroup mean differences between bar managers who owned venues and bar managers who only worked in venues, and between

smokers and non-smokers. These analyses are not presented but are available from authors. Briefly, they indicated measurement and relational invariance across held these subpopulations. It is the commonsense justice variables that are of primary importance for determining support for bar owners and bar managers, and smokers and non-smokers alike. Strategies of social marketers can frame the relevant issues for these subgroups collectively. In respect to the determinants of support, these groups are largely homogeneous.

While informative for politicians, health educationalists and social marketers, I anticipate my cross sectional findings to be of maximal interest to social marketers, deciding which aspects of the rights versus justice debate to frame in their social marketing campaigns, and health educationalists, interested in the influential but erroneous beliefs that impact public health. My findings suggest it is the justice constructs that should be emphasized by social marketers, and beliefs about ETS threats that should be targeted by health educationalists. I also note that the determinants of support were consistent over the three time points in the study. Framing endeavors that work prior to the ban are also likely to work after bans have been implemented.

Implications of longitudinal findings: Support increases over time and predicts enforcement behaviour!

The most powerful finding from my longitudinal results is that support for smoking bans increased linearly over the course of the study. Previous attempts at studying support for smoking bans have used just two snapshots – giving policy makers no indication of whether levels of support would reverse in the short to medium term. This new knowledge that support does not reverse will be comforting for policy makers who, as I have argued, have short to medium term interests in keeping their stakeholders satisfied. Also supporting previous research

(Sciacca, 1996) but improving on it by demonstrating consistent linearity over three waves, is the finding that beliefs about how difficult the legislation would be to enforce declined over the course of the study. Similarly, beliefs about the negative economic impacts of the legislation declined over the course of the study. Yet, these self interest constructs were shown in cross sectional modeling to be only modestly related to support. My observations of increasing support and its link to enforcement behavior aside, the next substantive point to emerge is the longitudinal change results in the justice component of my model. As hypothesized, the beliefs about the health threat posed by ETS did not change over the course of the study. This suggests educational aimed at intra-individual belief changes on this construct might be challenging. On the other hand, individuals' beliefs about the rights of workers and patrons to smoke-free work environments increased substantially. Given this finding, it may be most advantageous for health social marketers to frame the fairness angle of the model. Social marketers will be encouraged by workers' and patrons' rights to smoke free environments increasing, contrary to my hypotheses. From cross sectional models, I know these constructs mediate the relationship between ETS and the initial status and rate of change in support.

But why would policy makers care about whether stakeholders support smoking bans in the first place? The first reason is that I began with the premise that politicians wish to please their stakeholders in order to remain in power. Support is critical for this reason alone. But policy makers also want their policies to be successful. And to be successful, national smoking bans will require enforcement. The findings from my longitudinal study clearly show a statistically significant and sizable link between initial level of support for smoking bans and enforcement behaviour over the year since the smoking ban's introduction. Similarly, a significant and sizeable effect was observed between the rate of change in support over the year

and enforcement behaviour. The more you initially supported the ban, and the faster your support increased over the year, the more enforcement behaviour you reported being taken in your venue when violations of the smoking ban were observed. This draws attention to the practical import of stakeholder attitudes to smoking bans and to the value of identifying ways in which attitudes can be used to garner support for smoking bans. This finding also replicates and extends research showing the behavioral impact of attitudes in other domains, for example, the link between attitudes towards the death penalty and sentencing decisions in capital punishment cases (O'Neil, Patry & Penrod, 2004). Here again, it seems, attitudes matter.

Implications of mixture modeling findings

Growth mixture modeling of unobserved heterogeneity in the support growth process indicated that there were two distinct classes of individuals with respect to support for the legislation. The first class was a class that began with low support, and slowly decreased in support. The second class was a class that started with higher initial support, and increased rapidly. The likelihood of being in the increasing class was significantly higher for bar managers who believed that ETS was a real threat to health, and the high starting rapidly increasing class was characterized by a lower proportion of smokers and a higher degree of health related health problems than the low starting decreasing class. From a substantive perspective, these findings suggest it would be beneficial for social marketers to focus heavily on educating the public on the dangers of ETS, or perhaps what I have shown to be the more malleable mediators of the relation between ETS and support, patrons' and workers' rights. It also shows that while overall support increases over time, there is a class of bar managers, characterized by high smoking rates and low reported respiratory health issues, who begin with low support and slowly decrease. Policy makers will want to focus educational efforts around the dangers of ETS, and workers'

and patrons rights', on this 'stalwart' group. This finding would not have been uncovered were it not for the growth mixture modeling analyses.

Next steps in the implementation of a national smoking ban in the United States

So, what is to be done? The first step is for the research results of this study to be communicated to policy makers in a credible and widely read medium, such as this journal. Once this is done, I feel that policy makers will have a clearer understanding of what causes support and what happens to support over time. On this basis this study, I have shown that support for smoking bans consistently increases over the short to medium term. Politicians can therefore confidently implement such bans without fear of displeasing their stakeholders in the short to medium term. Once it is decided that a national smoking ban is to be implemented, social marketers and health educationalists can begin their work, framing the issue for the public as one of fairness, and educating about the dangers of ETS. Politicians must then look to the specific details of implementation, considering factors such as ways to reduce the perceived conflict between individual rights and public health amongst stakeholders, and methods for engendering cooperation amongst patrons. In the next section, I will outline some of the factors that are likely to influence the successful implementation of such bans.

Reducing the conflict between individual autonomy and public health through education

I tend to agree with Willemsen, Meijer, & Jannink (1999) in that there is no best way to implementing smoking policies, and that what differentiates successful and unsuccessful implementations of bans will depend on the nature of the ban and its context. However, Wilson and Thompson (2001) have provided useful suggestions about how the perceived curtailment of individual rights due to tobacco tax can be ameliorated, and I feel these approaches warrant

mention here. In relation to tobacco taxation rights conflict, they suggested public education involved (1) improving the quality of information provided to those affected by taxation, and how autonomy arguments differ for addictive products versus other products through mass media campaigns, (2) enhancing information around the role of government in protecting health in a democracy, and (3) being explicit that there is a tradeoff between individual rights and public good under smoking bans. The current research has demonstrated an important effect for beliefs about the dangers of ETS on commonsense justice and its subsequent link to support for the ban. Education about the threats posed by ETS will therefore be critical. But will information on these other aspects about smoking bans. Providing information in this fashion is a key step in a successful implementation of a national smoking ban. For example, being upfront about the rights tradeoff, I expect, is likely to promote trust, which has important consequences for cooperation (De Cremer & Tyler, 2007). It is also consistent with required political action implied results of Greenberg (1994), who observed an effect of informational justice on support for smoking bans.

Reducing the conflict between individual autonomy and public health through engagement

Willemsen, Meijer, & Jannink (1999) observed that confrontational bans result in decreased worker satisfaction with a smoking ban. This finding is also consistent with the work of Greenberg (1994). He showed that interactional justice was a key factors influencing workplace smoking ban support. Interactional justice, like informational justice, represents a social complement to distributive and procedural justice. Given the links observed in this study between support and subsequent enforcement behavior, it also suggests that a participative introduction of smoking bans is will be more likely to achieve a national ban's stated aims than if a national smoking ban was perceived by the major stakeholders to be autocratic. This reasoning

is supported by social dilemma research findings that repeatedly demonstrate group discussion of social dilemmas leads to increased individual cooperation (Hopthrow & Hulbert, 2005), due to the increased trust between groups from pursuit of a common goal (De Cremer & Stouten, 2004). When people feel part of a community, there is more likely to be restraint among users of natural resources (Van Vugt, 2002). When groups are engaged, they feel they have 'voice', and this enhances feelings of procedural fairness (Van den Bos, 1999), increasing cooperation (De Cremer & Tyler, 2007).

<u>Increasing compliance by engendering cooperative behaviour</u>

Throughout this thesis I have focused on whether bar managers believe that smoking bans violate commonsense notions of what is fair. I have argued that these notions of fairness represent outcomes rather than the processes by which they came about, or the social complements to procedural justice, i.e. interpersonal and interactional justice (Greenberg, 1993b; Colquitt, 2001). The focus on the effect of commonsense justice beliefs is largely due to the observational nature of my study, which was conducted in a national level setting. This did not permit control over these dimensional aspects of justice. There can be little doubt, however, that perceptions of these forms of justice would have an impact on individuals' support for a national ban. There is a substantial literature on the impact of these other aspects of justice on cooperation (see, for example, Folger, 1986a; Folger & Cropanzano, 2001; De Cremer & Tyler, 2007; De Cremer & Tyler, 2005), which will be required for a successful national ban. There is also a large literature on the effect of different forms of justice, and their interactions, on support for controversial policies like AAPs (Bobocel, Son-Hing, Davey, Stanley and Zanna, 1998), which could be usefully applied by politicians aiming to engender support. Maximizing support

and cooperation will need to surely be two of the primary aims of politicians implementing a national ban – and there is much to be learned from the justice literature in this respect.

Conclusions

These results suggest that I have a parsimonious model addressing my 12 hypotheses, which cover three research areas. This model was developed on the basis of relevant theory examined using robust statistical methods. My results suggested that the determinants of support for national smoking bans are common sense justice variables. My findings also show that support increases linearly over time. Finally, I demonstrated that the initial level of support, and the rate at which support increases, predict enforcement behaviour amongst this stakeholder group. I expect that this information will be particularly useful for three distinct groups of readers (1) politicians wishing to to know what happens to support for national bans in the short to medium term before implementing a national ban; (2) social marketers wanting to know what the key issues are that need to be framed in their social marketing campaigns; (3) public health educationalists wanting to know which erroneous beliefs are those that most influence support, and require the greatest focus by educational efforts. I hope that this work furthers the recent political debate over national smoking bans, contributes momentum toward implementation of such a ban in the United States, and provides useful suggestions over how such a ban might be implemented successfully.

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Appendix One: Mplus Syntax Files

Syntax example 1. Cross sectional measurement model

```
TITLE:  Time 1 cross sectional measurement model

DATA:
  FILE IS "Nigela.dat";

  FORMAT IS 117f3.0;

VARIABLE:


  NAMES ARE
   S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
    ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
    WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
    PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
    PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
    EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
    EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
    GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
    HEALTH3 ACTIONJ ACTIONN ENFORCE;

   USEVARIABLES ARE
    S1 S2 S3 S5
    ET1 ET2 ET3 ET4
    WR1 WR2 WR3 WR5
    PR3 PR4 PR5 PR1
    PI1 PI2 PI4 PI3
    EI1 EI4 EI5 EI2;

    MISSING = ALL (99);

  ANALYSIS:

    TYPE = MISSING H1;

    ESTIMATOR IS ML;

  MODEL:
        f1 BY S1
              S2
              S3
              s5;
        f2 BY ET1
              ET2
              ET3
              ET4;
        f3 BY WR1
              WR2
              WR3
              WR5;
        f4 BY PR3
              PR4
              PR5
              PR1;
        f5 BY PI1
              PI2
              PI4
              PI3;
        f6 BY EI1
              EI4
              EI5
              EI2;

OUTPUT: TECH4 TECH1 MODINDICES STANDARDIZED;
```

Syntax example 2. Cross sectional full structural model

```
TITLE: Time 1 full structural equation model

DATA:
  FILE IS "Nigela.dat";

  FORMAT IS 117f3.0;

VARIABLE:


  NAMES ARE
   S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
    ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
    WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
    PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
    PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
    EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
    EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
    GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
    HEALTH3 ACTIONJ ACTIONN ENFORCE;

   USEVARIABLES ARE
    S1 S2 S3 S5
    ET1 ET2 ET3 ET4
    WR1 WR2 WR3 WR5
    PR3 PR4 PR5 PR1
    PI1 PI2 PI4 PI3
    EI1 EI4 EI5 EI2;

    MISSING = ALL (99);

  ANALYSIS:

    TYPE = MISSING H1;

    ESTIMATOR IS ML;

  MODEL:
          f1 BY S1
                S2
                S3
                s5;
          f2 BY ET1
                ET2
                ET3
                ET4;
          f3 BY WR1
                WR2
                WR3
                WR5;
          f4 BY PR3
                PR4
                PR5
                PR1;
          f5 BY PI1
                PI2
                PI4
                PI3;
          f6 BY EI1
                EI4
                EI5
                EI2;

  f1 ON f6 (p1);
  f1 ON f5 (p2);
  f1 ON F4 (p3);
  f1 on F3 (p4);
  f3 ON f2 (p5);
```

```
  f4 ON f2 (p6);

MODEL INDIRECT:
f1 IND f2;
f1 IND f5;
f1 IND f6;

MODEL TEST:
0 = p1+p2-p3*p6-p4*p5;

OUTPUT: TECH4 TECH1 MODINDICES STANDARDIZED;
```

Syntax example 3. Cross sectional measurement invariance baseline (multiple group model)

```
TITLE:  Baseline model for owner-worker invariance

DATA:
  FILE IS "Nigela.dat";

  FORMAT IS 117f3.0;

VARIABLE:

    NAMES ARE
    S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
    ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
    WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
    PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
    PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
    EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
    EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
    GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
    HEALTH3 ACTIONJ ACTIONN ENFORCE;

  USEVARIABLES ARE S1 S2 S3 S5 ET1 ET2 ET3 ET4 WR1 WR2 WR3 WR5
  PR3 PR4 PR5 PR1 PI1 PI2 PI4 PI3 EI1 EI4 EI5 EI2;

  GROUPING IS WORK1 (1=OWN 2=WORK);

  MISSING = ALL (99);

ANALYSIS:

   TYPE = MEANSTRUCTURE;

MODEL:
        f1 BY S1
               S2
               S3
               S5;

        f2 BY ET1
               ET2
               ET3
               ET4;

        f3 BY WR1
               WR2
               WR3
               WR5;

        f4 BY PR3
               PR4
               PR5
               PR1;

        f5 BY PI1
               PI2
               PI4
               PI3;

        f6 BY EI1
               EI4
               EI5
               EI2;

        [S1 S2 S3 S5];
        [ET1 ET2 ET3 ET4];
        [WR1 WR2 WR3 WR5];
        [PR3 PR4 PR5 PR1];
        [PI1 PI2 PI4 PI3];
```

```
        [EI1 EI4 EI5 EI2];


MODEL OWN:

        f1 BY S2
              S3
              S5;

        f2 BY ET2
              ET3
              ET4;

        f3 BY WR2
              WR3
              WR5;

        f4 BY PR4
              PR5
              PR1;

        f5 BY PI2
              PI4
              PI3;

        f6 BY EI4
              EI5
              EI2;

        [S2 S3 S5];
        [ET2 ET3 ET4];
        [WR2 WR3 WR5];
        [PR4 PR5 PR1];
        [PI2 PI4 PI3];
        [EI4 EI5 EI2];

OUTPUT: TECH4 TECH1 MODINDICES STANDARDIZED;
```

Syntax example 4. Cross sectional measurement invariance metric (multiple group model)

```
TITLE:  Metric invariance model for owner-worker invariance

DATA:
  FILE IS "Nigela.dat";

  FORMAT IS 117f3.0;

VARIABLE:

    NAMES ARE
    S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
    ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
    WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
    PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
    PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
    EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
    EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
    GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
    HEALTH3 ACTIONJ ACTIONN;

  USEVARIABLES ARE S1 S2 S3 S5 ET1 ET2 ET3 ET4 WR1 WR2 WR3 WR5
  PR3 PR4 PR5 PR1 PI1 PI2 PI4 PI3 EI1 EI4 EI5 EI2;

  GROUPING IS WORK1 (1=WORK 2=OWN);

  MISSING = ALL (99);

ANALYSIS:

   TYPE = MEANSTRUCTURE;

MODEL:
        f1 BY S1
               S2
               S3
               S5;

        f2 BY ET1
               ET2
               ET3
               ET4;

        f3 BY WR1
               WR2
               WR3
               WR5;

        f4 BY PR3
               PR4
               PR5
               PR1;

        f5 BY PI1
               PI2
               PI4
               PI3;

        f6 BY EI1
               EI4
               EI5
               EI2;

        [S1 S2 S3 S5];
        [ET1 ET2 ET3 ET4];
        [WR1 WR2 WR3 WR5];
        [PR3 PR4 PR5 PR1];
        [PI1 PI2 PI4 PI3];
```

```
        [EI1 EI4 EI5 EI2];

MODEL OWN:

        [S2 S3 S5];
        [ET2 ET3 ET4];
        [WR2 WR3 WR5];
        [PR4 PR5 PR1];
        [PI2 PI4 PI3];
        [EI4 EI5 EI2];

OUTPUT: TECH4 TECH1 MODINDICES STANDARDIZED;
```

Syntax example 5. Cross sectional measurement invariance scalar (multiple group model)

```
TITLE:  Metric invariance model for owner-worker invariance

DATA:
  FILE IS "Nigela.dat";

  FORMAT IS 117f3.0;

VARIABLE:

   NAMES ARE
   S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
   ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
   WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
   PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
   PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
   EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
   EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
   GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
   HEALTH3 ACTIONJ ACTIONN;

  USEVARIABLES ARE S1 S2 S3 S5 ET1 ET2 ET3 ET4 WR1 WR2 WR3 WR5
  PR3 PR4 PR5 PR1 PI1 PI2 PI4 PI3 EI1 EI4 EI5 EI2;

  GROUPING IS WORK1 (1=WORK 2=OWN);

  MISSING = ALL (99);

ANALYSIS:

   TYPE = MEANSTRUCTURE;

MODEL:
        f1 BY S1
               S2
               S3
               S5;

        f2 BY ET1
               ET2
               ET3
               ET4;

        f3 BY WR1
               WR2
               WR3
               WR5;

        f4 BY PR3
               PR4
               PR5
               PR1;

        f5 BY PI1
               PI2
               PI4
               PI3;

        f6 BY EI1
               EI4
               EI5
               EI2;

        [S1 S2 S3 S5];
        [ET1 ET2 ET3 ET4];
        [WR1 WR2 WR3 WR5];
        [PR3 PR4 PR5 PR1];
        [PI1 PI2 PI4 PI3];
```

```
        [EI1 EI4 EI5 EI2];

MODEL OWN:


OUTPUT: TECH4 TECH1 MODINDICES STANDARDIZED;
```

Syntax example 6. Cross sectional measurement invariance error (multiple group model)

```
TITLE:  Error equivalence for owner-worker invariance model

DATA:
  FILE IS "Nigela.dat";

  FORMAT IS 117f3.0;

VARIABLE:

    NAMES ARE
    S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
    ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
    WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
    PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
    PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
    EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
    EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
    GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
    HEALTH3 ACTIONJ ACTIONN;

  USEVARIABLES ARE S1 S2 S3 S5 ET1 ET2 ET3 ET4 WR1 WR2 WR3 WR5
  PR3 PR4 PR5 PR1 PI1 PI2 PI4 PI3 EI1 EI4 EI5 EI2;

  GROUPING IS WORK1 (1=WORK 2=OWN);

  MISSING = ALL (99);

ANALYSIS:

   TYPE = MEANSTRUCTURE;

MODEL:
        f1 BY S1
              S2
              S3
              S5;

        f2 BY ET1
              ET2
              ET3
              ET4;

        f3 BY WR1
              WR2
              WR3
              WR5;

        f4 BY PR3
              PR4
              PR5
              PR1;

        f5 BY PI1
              PI2
              PI4
              PI3;

        f6 BY EI1
              EI4
              EI5
              EI2;

        [S1 S2 S3 S5];
        [ET1 ET2 ET3 ET4];
        [WR1 WR2 WR3 WR5];
        [PR3 PR4 PR5 PR1];
        [PI1 PI2 PI4 PI3];
```

```
        [EI1 EI4 EI5 EI2];

S1 (1);
s2 (2);
s3 (3);
s5 (4);
ET1 (5);
ET2 (6);
ET3 (7);
ET4 (8);
WR1 (9);
WR2 (10);
WR3 (11);
WR5 (12);
PR3 (13);
PR4 (14);
PR5 (15);
PR1 (16);
PI1 (17);
PI2 (18);
PI4 (19);
PI3 (20);
EI1 (21);
EI4 (22);
EI5 (23);
EI2 (24);


MODEL OWN:

S1 (1);
s2 (2);
s3 (3);
s5 (4);
ET1 (5);
ET2 (6);
ET3 (7);
ET4 (8);
WR1 (9);
WR2 (10);
WR3 (11);
WR5 (12);
PR3 (13);
PR4 (14);
PR5 (15);
PR1 (16);
PI1 (17);
PI2 (18);
PI4 (19);
PI3 (20);
EI1 (21);
EI4 (22);
EI5 (23);
EI2 (24);

OUTPUT: TECH4 TECH1 MODINDICES STANDARDIZED;
```

Syntax example 7. Cross sectional measurement invariance error (multiple group model)

```
TITLE:  Relational Equivalennce for owner-worker invariance model


DATA:
  FILE IS "Nigela.dat";

  FORMAT IS 117f3.0;

VARIABLE:

    NAMES ARE
    S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
    ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
    WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
    PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
    PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
    EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
    EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
    GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
    HEALTH3 ACTIONJ ACTIONN;

  USEVARIABLES ARE S1 S2 S3 S5 ET1 ET2 ET3 ET4 WR1 WR2 WR3 WR5
  PR3 PR4 PR5 PR1 PI1 PI2 PI4 PI3 EI1 EI4 EI5 EI2;

  GROUPING IS WORK1 (1=WORK 2=OWN);

  MISSING = ALL (99);

ANALYSIS:

   TYPE = MEANSTRUCTURE;

MODEL:
        f1 BY S1
               S2
               S3
               S5;

        f2 BY ET1
               ET2
               ET3
               ET4;

        f3 BY WR1
               WR2
               WR3
               WR5;

        f4 BY PR3
               PR4
               PR5
               PR1;

        f5 BY PI1
               PI2
               PI4
               PI3;

        f6 BY EI1
               EI4
               EI5
               EI2;

        [S1 S2 S3 S5];
        [ET1 ET2 ET3 ET4];
        [WR1 WR2 WR3 WR5];
        [PR3 PR4 PR5 PR1];
```

```
        [PI1 PI2 PI4 PI3];
        [EI1 EI4 EI5 EI2];


f1 on f5;
f1 on f6;
f1 on f3;
f1 on f4;
f3 on f2;
f4 on f2;

MODEL OWN:

f1 on f5;
f1 on f6;
f1 on f3;
f1 on f4;
f3 on f2;
f4 on f2;

OUTPUT: TECH4 TECH1 MODINDICES STANDARDIZED;
```

Syntax example 8. Longitudinal invariance model (single group model)

```
TITLE:  Time 1 and 2 longitudinal invariance


DATA:
  FILE IS "Nigela.dat";

  FORMAT IS 117f3.0;

VARIABLE:


  NAMES ARE
   S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
    ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
    WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
    PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
    PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
    EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
    EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
    GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
    HEALTH3 ACTIONJ ACTIONN ENFORCE;

   USEVARIABLES ARE
    S1 S2 S3 S5 S7 S8 S9 S11
    !ET1 ET2 ET3 ET4 ET6 ET7 ET8 ET9
    !WR1 WR2 WR3 WR5 WR6 WR7 WR8 WR10
    !PR3 PR4 PR5 PR1 PR8 PR9 PR10 PR6
    PI1 PI2 PI3 PI4 PI6 PI7 PI8 PI9;
    !EI1 EI2 EI3 EI4 EI7 EI10 EI11 EI18;

   MISSING = ALL (99);

  ANALYSIS:
    TYPE = GENERAL;

    ESTIMATOR IS ML;

  MODEL:
        f1 BY  S1
               S2  (1)
               S3  (2)
               s5  (3);
        f2 BY  S7
               S8  (1)
               S9  (2)
               S11 (3);
    !     f3 BY  ET1
    !             ET2
    !             ET3
    !             ET4;
    !     f4 BY  ET6
    !             ET7
    !             ET8
    !             ET9;
    !     f5 BY  WR1
    !             WR2
    !             WR3
    !             WR5;
    !     f6 BY  WR6
    !             WR7
    !             WR8
    !             WR10;
    !     f7 BY  PR3
    !             PR4
    !             PR5
    !             PR1;
    !     f8 BY  PR8
    !             PR9
```

```
    !              PR10
    !              PR6;
        f9 BY  PI1
               PI2 (4)
               PI3 (5)
               PI4 (6);
        f10 BY PI6
               PI7 (4)
               PI8 (5)
               PI9 (6);
    !   f11 BY EI1
    !          EI2
    !          EI3
    !          EI4;
    !   f12 BY EI7
    !          EI10
    !          EI11
    !          EI18;

! example of testing equivalence of personal implications to support
! path over times one and two.

f1 on f9  (7);
f2 on f10 (7);
OUTPUT: TECH4 STANDARDIZED;
```

Syntax example 9. Unconditional growth model example

```
TITLE:  Multiple-Indicator Linear Growth Model for Support

DATA:
  FILE IS "Nigela.dat";

  FORMAT IS 117f3.0;

VARIABLE:

     NAMES ARE
    S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
    ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
    WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
    PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
    PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
    EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
    EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
    GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
    HEALTH3 ACTIONJ ACTIONN;

  USEVARIABLES ARE S1 S3 S5 S7 S9 S11 S13 S15 S17 ;

  MISSING = ALL (99);

ANALYSIS:

  TYPE = MISSING H1;

MODEL:
        f1 BY S1
             S3  (1)
             S5  (2);
        f2 BY S7
             S9  (1)
             S11 (2);
        f3 BY S13
             S15 (1)
             S17 (2);

        [S1 S7 S13]  (3);
        [S3 S9 S15]  (4);
        [S5 S11 S17] (5);

i s | f1@0 f2@1 f3@2;

! non-significant third factor residual fixed at zero

F3@0;

PLOT:

TYPE IS PLOT3;
SERIES = F1(s) F2(s) F3(s);

OUTPUT: TECH4 TECH1 MODINDICES STANDARDIZED;
```

Syntax example 10. Conditional growth model example

```
TITLE:  Embedded Multiple Indicator Linear Growth Model

DATA:
  FILE IS "Nigela.dat";

  FORMAT IS 117f3.0;

VARIABLE:

   NAMES ARE
   S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
   ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
   WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
   PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
   PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
   EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
   EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
   GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
   HEALTH3 ACTIONN ACTIONJ ENFORCE;

  USEVARIABLES ARE S1 S3 S5 S7 S9 S11 S13 S15 S17 ET1 ET2 ET3 health1
  health2 health3 smoke1 smoke2 smoke3 ENFORCE;

  CATEGORICAL ARE S1 S3 S5 S7 S9 S11 S13 S15 S17 ET1 ET2 ET3 ENFORCE;

  MISSING = ALL (99);

ANALYSIS:


  TYPE = MISSING H1;

  ESTIMATOR IS WLSMV;

MODEL:
        f1 BY S1
              S3   (1)
              S5   (2);
        f2 BY S7
              S9   (1)
              S11  (2);
        f3 BY S13
              S15  (1)
              S17  (2);

        [S1$1 S7$1 S13$1]  (3);
        [S3$1 S9$1 S15$1]  (4);
        [S5$1 S11$1 S17$1] (5);
        {S1-S5@1, S7-S17};

i s | f1@0 f2@1 f3@2;

f1-f3 (6);

        f4 BY ET1
              ET2
              ET3;

f1 on health1 (6);
f2 on health2 (6);
f3 on health3 (6);

f1 on smoke1 (7);
f2 on smoke2 (7);
f3 on smoke3 (7);

i on f4;
```

```
!s on f4;

ENFORCE on i (8);
ENFORCE on s (8);

PLOT:

TYPE IS PLOT3;
SERIES = F1(s) F2(s) F3(s);

OUTPUT: TECH4 TECH1 STANDARDIZED;
```

Syntax example 11.   Unconditional growth mixture model example – 2 class

```
TITLE:  Two Class Growth Mixture Model for Support
DATA:
  FILE IS "Nigela.dat";
  FORMAT IS 117f3.0;

VARIABLE:

  NAMES ARE
  S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
  ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
  WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
  PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
  PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
  EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
  EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
  GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
  HEALTH3 ACTIONN ACTIONJ ENFORCE;

  USEVARIABLES ARE S1 S3 S5 S7 S9 S11 S13 S15 S17;

  CLASSES = C (2);

  MISSING = ALL (99);

ANALYSIS:

    TYPE = MIXTURE MISSING;
    ESTIMATOR = MLR;
    ALGORITHM=INTEGRATION;
    STARTS = 500 20;
    STITERATIONS = 20;
    LRTSTARTS = 10 5 100 50;

MODEL:

%OVERALL%

        f1 BY S1
              S3   (1)
              S5   (2);
        f2 BY S7
              S9   (1)
              S11  (2);
        f3 BY S13
              S15  (1)
              S17  (2);
         f3@0;

        [S1 S7 S13]  (3);
        [S3 S9 S15]  (4);
        [S5 S11 S17] (5);

        i s | f1@0 f2@1 f3@2;

PLOT:

TYPE IS PLOT3;

SERIES = F1(s) F2(s) F3(s);

OUTPUT: STANDARDIZED tech1 tech4 tech11 tech13 tech14;
```

Syntax example 12. Unconditional growth mixture model example – 3 class

```
TITLE:  Three Class Growth Mixture Model
DATA:
  FILE IS "Nigela.dat";
  FORMAT IS 117f3.0;

VARIABLE:

  NAMES ARE
  S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
  ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
  WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
  PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
  PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
  EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
  EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
  GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
  HEALTH3 ACTIONN ACTIONJ ENFORCE;

  USEVARIABLES ARE S1 S3 S5 S7 S9 S11 S13 S15 S17;

  CLASSES = C (3);

  MISSING = ALL (99);

ANALYSIS:

    TYPE = MIXTURE MISSING;
    ESTIMATOR = MLR;
    ALGORITHM=INTEGRATION;
    STARTS = 500 20;
    STITERATIONS = 20;
    LRTSTARTS = 10 5 100 50;

MODEL:

%OVERALL%

        f1 BY S1
            S3    (1)
            S5    (2);
        f2 BY S7
            S9    (1)
            S11   (2);
        f3 BY S13
            S15   (1)
            S17   (2);
         f3@0;

        [S1 S7 S13]  (3);
        [S3 S9 S15]  (4);
        [S5 S11 S17] (5);

        i s | f1@0 f2@1 f3@2;

PLOT:

TYPE IS PLOT3;

SERIES = F1(s) F2(s) F3(s);

OUTPUT: STANDARDIZED tech1 tech4 tech11 tech13 tech14;
```

Syntax example 13. Unconditional growth mixture model example – 4 class

```
TITLE:  Four Class Growth Mixture Model for Support
DATA:
  FILE IS "Nigela.dat";
  FORMAT IS 117f3.0;

VARIABLE:

  NAMES ARE
  S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
  ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
  WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
  PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
  PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
  EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
  EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
  GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
  HEALTH3 ACTIONN ACTIONJ ENFORCE;

  USEVARIABLES ARE S1 S3 S5 S7 S9 S11 S13 S15 S17;

  CLASSES = C (3);

! CATEGORICAL ARE ALL;

  MISSING = ALL (99);

ANALYSIS:

    TYPE = MIXTURE MISSING;
    ESTIMATOR = MLR;
    ALGORITHM=INTEGRATION;
    STARTS = 500 20;
    STITERATIONS = 20;
    LRTSTARTS = 10 5 100 50;

MODEL:

%OVERALL%

        f1 BY S1
            S3   (1)
            S5   (2);
        f2 BY S7
            S9   (1)
            S11  (2);
        f3 BY S13
            S15  (1)
            S17  (2);
        f3@0;

        [S1 S7 S13]  (3);
        [S3 S9 S15]  (4);
        [S5 S11 S17] (5);

        i s | f1@0 f2@1 f3@2;

PLOT:

TYPE IS PLOT3;

SERIES = F1(s) F2(s) F3(s);

OUTPUT: STANDARDIZED tech1 tech4 tech11 tech13 tech14;
```

Syntax example 14. Conditional growth mixture model example – 2 class

```
TITLE:  Two Class General Growth Mixture Model
DATA:
  FILE IS "Nigela.dat";
  FORMAT IS 117f3.0;

VARIABLE:

  NAMES ARE
  S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
  ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
  WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
  PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
  PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
  EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
  EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
  GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
  HEALTH3 ACTIONN ACTIONJ ENFORCE;

  USEVARIABLES ARE S1 S3 S5 S7 S9 S11 S13 S15 S17 ET1 ET2 ET3
  ENFORCE SMOKE1 SMOKE2 SMOKE3 HEALTH1 HEALTH2 HEALTH3;

  CLASSES = C (2);

  CATEGORICAL IS ENFORCE;

  MISSING = ALL (99);

ANALYSIS:

    TYPE = MIXTURE MISSING;
    ESTIMATOR = MLR;
    ALGORITHM=INTEGRATION;
    STARTS = 500 20;
    STITERATIONS = 20;
    LRTSTARTS = 10 5 100 50;

MODEL:

%OVERALL%

        f1 BY S1
             S3   (1)
             S5   (2);
        f2 BY S7
             S9   (1)
             S11  (2);
        f3 BY S13
             S15  (1)
             S17  (2);
        f3@0;

        [S1 S7 S13]  (3);
        [S3 S9 S15]  (4);
        [S5 S11 S17] (5);

        i s | f1@0 f2@1 f3@2;

        f4 BY ET1
             ET2
             ET3;

i on f4;

f1 on health1 (6);
f2 on health2 (6);
f3 on health3 (6);

f1 on smoke1 (7);
```

```
f2 on smoke2 (7);
f3 on smoke3 (7);

c#1 on F4;

PLOT:

TYPE IS PLOT3;

SERIES = F1(s) F2(s) F3(s);

OUTPUT: STANDARDIZED tech1 tech4 tech11 tech13 tech14;
```

Syntax example 15. Conditional growth mixture model example – 3 class

```
TITLE:  Three Class General Growth Mixture Model
DATA:
  FILE IS "Nigela.dat";
  FORMAT IS 117f3.0;

VARIABLE:

  NAMES ARE
  S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
  ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
  WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
  PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
  PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
  EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
  EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
  GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
  HEALTH3 ACTIONN ACTIONJ ENFORCE;

  USEVARIABLES ARE S1 S3 S5 S7 S9 S11 S13 S15 S17 ET1 ET2 ET3
  ENFORCE SMOKE1 SMOKE2 SMOKE3 HEALTH1 HEALTH2 HEALTH3;

  CLASSES = C (3);

  CATEGORICAL IS ENFORCE;

  MISSING = ALL (99);

ANALYSIS:

    TYPE = MIXTURE MISSING;
    ESTIMATOR = MLR;
    ALGORITHM=INTEGRATION;
    STARTS = 500 20;
    STITERATIONS = 20;
    LRTSTARTS = 10 5 100 50;

MODEL:

%OVERALL%

        f1 BY S1
              S3   (1)
              S5   (2);
        f2 BY S7
              S9   (1)
              S11  (2);
         f3 BY S13
              S15  (1)
              S17  (2);
         f3@0;

        [S1 S7 S13]  (3);
        [S3 S9 S15]  (4);
        [S5 S11 S17] (5);

        i s | f1@0 f2@1 f3@2;

         f4 BY ET1
              ET2
              ET3;

i on f4;

f1 on health1 (6);
f2 on health2 (6);
f3 on health3 (6);

f1 on smoke1 (7);
```

```
f2 on smoke2 (7);
f3 on smoke3 (7);

c#1 on F4;
c#2 on F4;

PLOT:

TYPE IS PLOT3;

SERIES = F1(s) F2(s) F3(s);

OUTPUT: STANDARDIZED tech1 tech4 tech11 tech13 tech14;
```

Syntax example 16. Conditional growth mixture model example – 4 class

```
TITLE:  Four Class General Growth Mixture Model
DATA:
  FILE IS "Nigela.dat";
  FORMAT IS 117f3.0;

VARIABLE:

  NAMES ARE
  S1 S2 S3 S4 S5 S6 S7 S8 S9 S10 S11 S12 S13 S14 S15 S16 S17 S18
  ET1 ET2 ET3 ET4 ET5 ET6 ET7 ET8 ET9 ET10 ET11 ET12 ET13 ET14 ET15
  WR1 WR2 WR3 WR4 WR5 WR6 WR7 WR8 WR9 WR10 WR11 WR12 WR13 WR14 WR15
  PR1 PR2 PR3 PR4 PR5 PR6 PR7 PR8 PR9 PR10 PR11 PR12 PR13 PR14 PR15
  PI1 PI2 PI3 PI4 PI5 PI6 PI7 PI8 PI9 PI10 PI11 PI12 PI13 PI14 PI15
  EI1 EI2 EI3 EI4 EI5 EI6 EI7 EI8 EI9 EI10 EI11 EI12 EI13 EI14 EI15
  EI16 EI17 EI18 location seenJ actedJ seenN actedN out1 out2 out3
  GENDER SMOKE1 SMOKE2 SMOKE3 work1 work2 work3 HEALTH1 HEALTH2
  HEALTH3 ACTIONN ACTIONJ ENFORCE;

  USEVARIABLES ARE S1 S3 S5 S7 S9 S11 S13 S15 S17 ET1 ET2 ET3
  ENFORCE SMOKE1 SMOKE2 SMOKE3 HEALTH1 HEALTH2 HEALTH3;

  CLASSES = C (4);

  CATEGORICAL IS ENFORCE;

  MISSING = ALL (99);

ANALYSIS:

    TYPE = MIXTURE MISSING;
    ESTIMATOR = MLR;
    ALGORITHM=INTEGRATION;
    STARTS = 500 20;
    STITERATIONS = 20;
    LRTSTARTS = 10 5 100 50;

MODEL:

%OVERALL%

        f1 BY S1
            S3   (1)
            S5   (2);
        f2 BY S7
            S9   (1)
            S11  (2);
        f3 BY S13
            S15  (1)
            S17  (2);
        f3@0;

        [S1 S7 S13]  (3);
        [S3 S9 S15]  (4);
        [S5 S11 S17] (5);

        i s | f1@0 f2@1 f3@2;

        f4 BY ET1
            ET2
            ET3;

i on f4;

f1 on health1 (6);
f2 on health2 (6);
f3 on health3 (6);

f1 on smoke1 (7);
```

```
f2 on smoke2 (7);
f3 on smoke3 (7);

c#1 on F4;
c#2 on F4;
c#3 on F4;

PLOT:

TYPE IS PLOT3;

SERIES = F1(s) F2(s) F3(s);

OUTPUT: STANDARDIZED tech1 tech4 tech11 tech13 tech14;
```